Dynamic Data Driven Applications Systems (DDDAS)

Date: 06 March 2013

Frederica Darema, Ph. D., IEEE Fellow
Program Officer
AFOSR/RTC
Air Force Research Laboratory

Integrity ★ Service ★ Excellence

Report Documentation Page

Form Approved
OMB No. 0704-0188

1. REPORT DATE **06 MAR 2013**	2. REPORT TYPE	3. DATES COVERED **00-00-2013 to 00-00-2013**

4. TITLE AND SUBTITLE **Dynamic Data Driven Applications Systems (DDDAS)**	5a. CONTRACT NUMBER
	5b. GRANT NUMBER
	5c. PROGRAM ELEMENT NUMBER
6. AUTHOR(S)	5d. PROJECT NUMBER
	5e. TASK NUMBER
	5f. WORK UNIT NUMBER
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) **Air Force Office of Scientific Research ,AFOSR/RTC,875 N. Randolph,Arlington,VA,22203**	8. PERFORMING ORGANIZATION REPORT NUMBER
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)	10. SPONSOR/MONITOR'S ACRONYM(S)
	11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION/AVAILABILITY STATEMENT
Approved for public release; distribution unlimited

13. SUPPLEMENTARY NOTES
Presented at the AFOSR Spring Review 2013, 4-8 March, Arlington, VA.

14. ABSTRACT

15. SUBJECT TERMS

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT **unclassified**	b. ABSTRACT **unclassified**	c. THIS PAGE **unclassified**	**Same as Report (SAR)**	**43**	

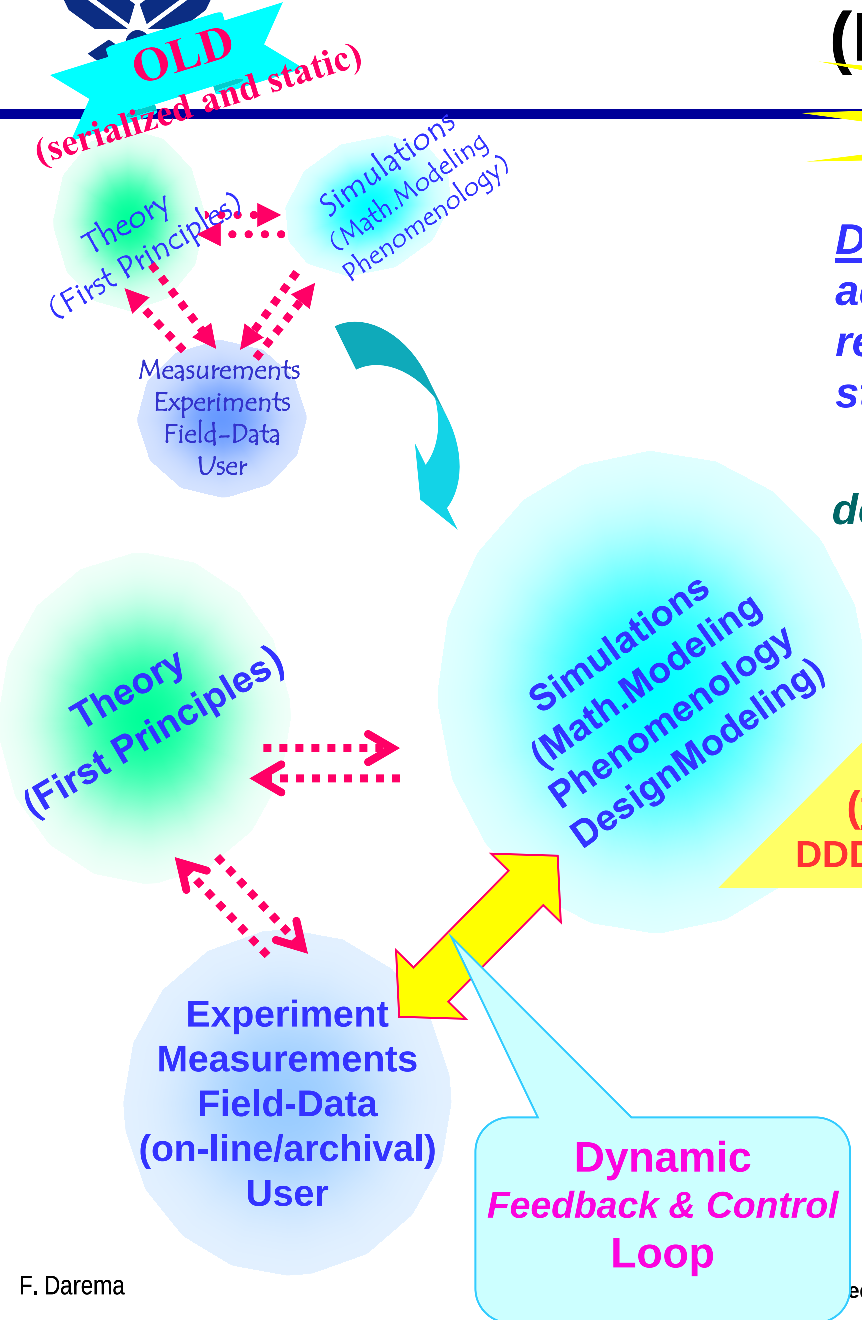
PROGRAM NAME: Dynamic Data Driven Applications Systems (DDDAS)

BRIEF DESCRIPTION OF PORTFOLIO:
Advanced methods for applications modeling/simulation and instrumentation (sensoring/control); dynamic/adaptive runtime supporting integrated computational environments spanning and unifying the high-end with the real-time data acquisition and control

LIST SUB-AREAS IN PORTFOLIO:
- **Application Modeling/Simulation**
- **Application Algorithms**
- **Systems Software**
- **Instrumentation Methods**

- **New Program – announced in AFSOR BAA-2011** (posted in Spring2011)
- **Projects awarded in 4QFY11 and 3QFY12**

Dynamic Data Driven Applications Systems (DDDAS)



InfoSymbiotic Systems

***DDDAS**: ability to dynamically incorporate additional data into an executing application, and in reverse, ability of an application to dynamically steer the measurement process*

"revolutionary" concept enabling
design, build, manage, understand complex systems

Dynamic Integration of
Computation & Measurements/Data
Unification of
Computing Platforms & Sensors/Instruments
(from the High-End to the Real-Time,to the PDA)
DDDAS – architecting & adaptive mngmnt of sensor systems

***Challenges*:**
Application Simulations Methods
Algorithmic Stability
Measurement/Instrumentation Methods
Computing Systems Software Support

Synergistic, Multidisciplinary Research

Advances in Capabilities through DDDAS
Timeliness
and Fundamental Science and Technology Challenges for Enabling DDDAS Capabilities

- **DDDAS: integration of application simulation/models with the application instrumentation components in a dynamic feed-back control loop**
  - **speedup of the simulation, by replacing computation with data in specific parts of the phase-space of the application**

    and/or
  - **augment model with actual data to improve accuracy of the model, improve analysis/prediction capabilities of application models**
  - **dynamically manage/schedule/architect heterogeneous resources, such as:**
    - **networks of heterogeneous sensors, or networks of heterogeneous controllers**
  - **enable ~decision-support capabilities w simulation-modeling accuracy**
- **unification from the high-end to the real-time data acquisition**
- **Increased Computation/Communication capabilities; ubiquitous heterogeneous sensoring**
- **Application modeling (in the context of dynamic data inputs)**
  - **dynamically invoke/select appropriate application components (models/algori) depend g on streamed data; interfacing applications with measurement system**

    multi-modal, multi-scale – dynamically invoke multip cales/modalities

    dynamic hierarchical decomposition (computational platfo) on
- **Algorithms**
  - **tolerant to perturbations of dynamic data inputs - UC**
- **Measurements**
  - **multiple modalities, space/time-distributed, heterogene**
- **Systems supporting dynamic runtime environm nts**
  - **extended spectrum of platforms (*beyond traditional computati nal gri o include sensor grids*)**
  - **dynamic execution support on heterogeneous environments**

DDDAS/InfoSymbiotics

is the unifying paradigm

Examples of Projects from DDDAS/AFOSR BAA
(awarded in 4QFY11 and 3QFY12)

- **Context of Key Strategic Approaches of the Program**
  - **Multidisciplinary Research**
  - **Focus of advancing capabilities along the Key Areas identified in the Technology Horizons and the Energy Horizons Reports**

DDDAS … key concept in many of the objectives set in Technology Horizons

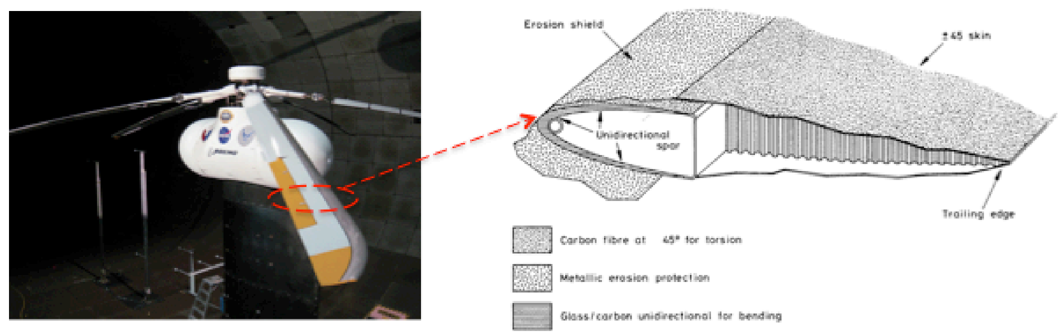
- ☐Autonomous systems
- ☐Autonomous reasoning and learning
- ☐Resilient autonomy
- ☐Complex adaptive systems
- ☐V&V for complex adaptive systems
- ☐Collaborative/cooperative control
- ☐Autonomous mission planning
- ☐Cold-atom INS
- ☐Chip-scale atomic clocks
- ☐Ad hoc networks
- ☐Polymorphic networks
- ☐Agile networks
- ☐Laser communications
- ☐Frequency-agile RF systems
- ☐Spectral mutability
- ☐Dynamic spectrum access
- ☐Quantum key distribution
- ☐Multi-scale simulation technologies
- ☐Coupled multi-physics simulations
- ☐Embedded diagnostics
- ☐Decision support tools
- ☐Automated software generation
- ☐Sensor-based processing
- ☐Behavior prediction and anticipation
- ☐Cognitive modeling
- ☐Cognitive performance augmentation
- ☐Human-machine interfaces

Advanced Simulation, Optimization, and Health Monitoring of Large Scale Structural Systems

Y. Bazilevs, A.L. Marsden, F. Lanza di Scalea, A. Majumdar, and M. Tatineni (UCSD)

- **Main Objective:**
  A Computational Steering Framework for Large-Scale Composite Structures & Environment-coupled, based on Continually and Dynamically Injected Sensor Data

- **Key Features:**
  - **A structural health monitoring (SHM) system**
  - **Simulation model of a structural system with fluid-structure interaction (FSI)**
  - **Sensitivity analysis, optimization and control software module**
  - **Implementation framework in high-performance computing (HPC) environments**
  - **Integration of FSI, SHM, sensitivity analysis, optimization, control, and HPC into a unified DDDAS framework**



<u>**Advanced Simulation Model:**</u>
1. Simulate full-scale, 3D, time-dependent FSI
2. Use a structural model with built-in damage from SHM data

<u>**Structural Health Monitoring:**</u>
1. Structural damage detection and quantification
2. Assessment of the remaining fatigue life of the structure

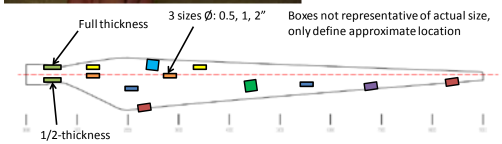
<u>**Sensitivity analysis, optimization and control:**</u>
1. Assess the sensitivity of the quantities of interest due to uncertainty in input damage parameters.
2. Optimize structure operating conditions to minimize further damage and increase structure remaining fatigue life

Advanced Simulation, Optimization, and Health Monitoring of Large Scale Structural Systems

Y. Bazilevs, A.L. Marsden, F. Lanza di Scalea, A. Majumdar, and M. Tatineni (UCSD)

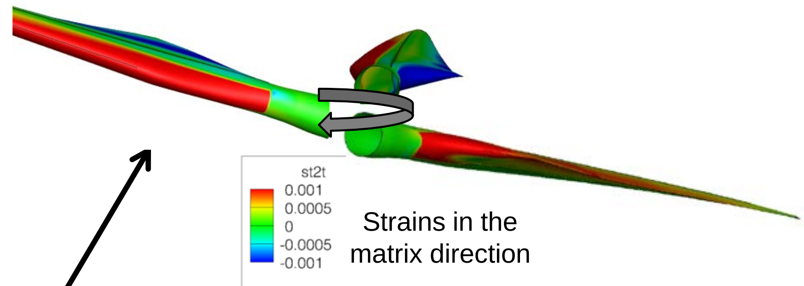
DDAS Loop for Detected In-plane Waviness

SENSOR DATA/
MEASUREMENTS



Request for additional or refined sensor data

IGA SIMULATION



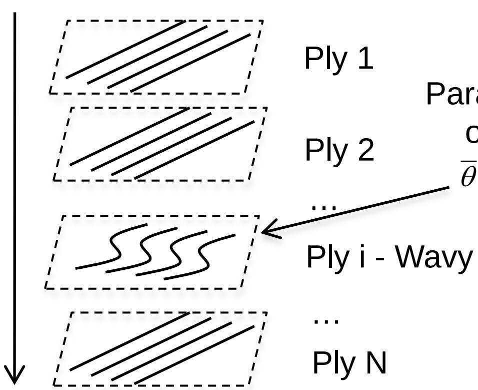
Strains in the matrix direction

Defect detection, geometry and type

Input for analysis, data for mesh refinement based on error indicators

IGA MESHING AND PREPROCESSING

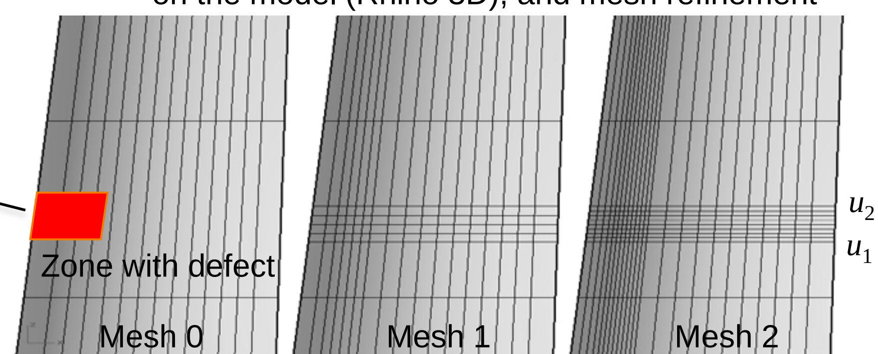
Through-thickness homogenization



Parametric description of fiber waviness

$$\overline{\theta} + \theta_{dev} \sin\left(2\pi \frac{u - u_1}{u_2 - u_1}\right)$$

Waviness zone and ply identification on the model (Rhino 3D), and mesh refinement



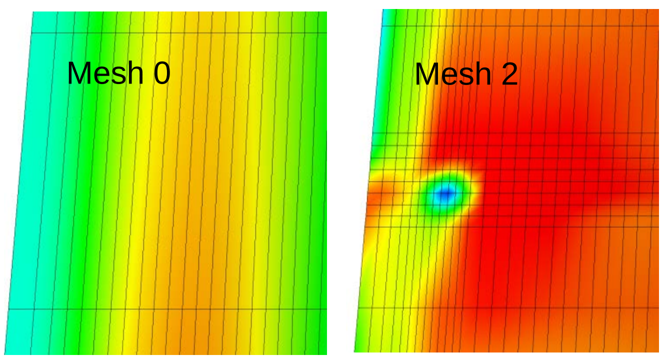
Y. Bazilevs, A.L. Marsden, F. Lanza di Scalea, A. Majumdar, and M. Tatineni (UCSD)

Fiber Waviness Computation Results

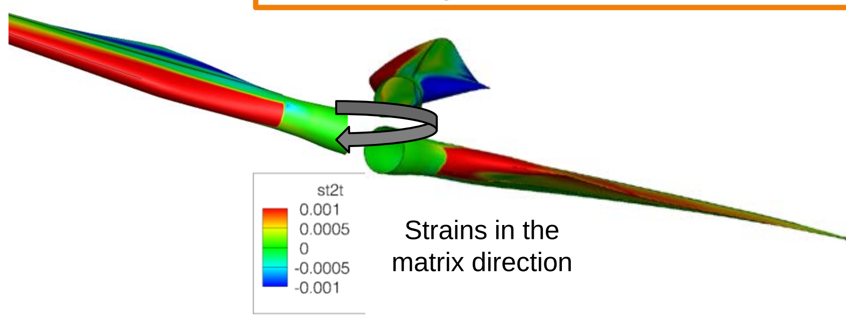
SHM
Detected defect on a 12x12cm zone near trailing edge

Damage Diagnosis
Defect corresponds to **waviness of composite fibers** in the outer layer of the blade laminate

Preprocessing/Meshing
1. Identified parametric coordinates of the defect region on the blade surface
2. **Parametrically modeled** fiber waviness
3. Re-homogenized material properties
4. **Locally refined mesh** to better capture stress magnitude and variation



Local mesh refinement captured stress concentration due to detected defect!!!

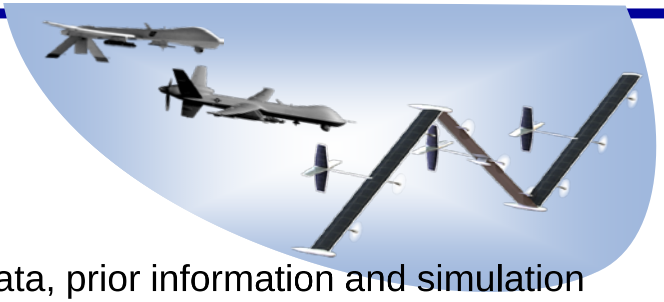


Simulation
1. **Inserted** new material data into a running calculation of a spinning blade
2. **Detected significant changes** in the stress levels in the region with defect
3. Refined mesh, re-interpolated solution and material data, and resumed computation

Decision
Stress levels detected in the region with defect are sufficiently lower than the critical to stop operation. Normal operation is resumed.

Dynamic Data-Driven Methods for Self-Aware Aerospace Vehicles

D Allaire, L Mainini, F Ulker, M Lecerf, H Li, K Willcox (MIT); G Biros, O Ghattas (UT Austin);
J Chambers, R Cowlagi, D Kordonowy (Aurora)



A self-aware aerospace vehicle can dynamically adapt the way it performs missions by gathering information about itself and its surroundings and responding intelligently.

Approach and objectives

- **infer** vehicle health and state through dynamic integration of sensed data, prior information and simulation models
- **predict** flight limits through updated estimates using adaptive simulation models
- **re-plan** mission with updated flight limits and health-awareness based on sensed environmental data

Research Goal: **Create a multifidelity framework for the DDAS paradigm**

- DDDAS process draws on multiple modeling options and data sources to evolve models, sensing strategies, and predictions as the flight proceeds
- Dynamic data inform online adaptation of structural damage models and reduced-order models
- Dynamic guidance of sensing strategies
- Dynamic, online management of multifidelity structural response models and sensor data, ensuring that predictions have sufficient confidence

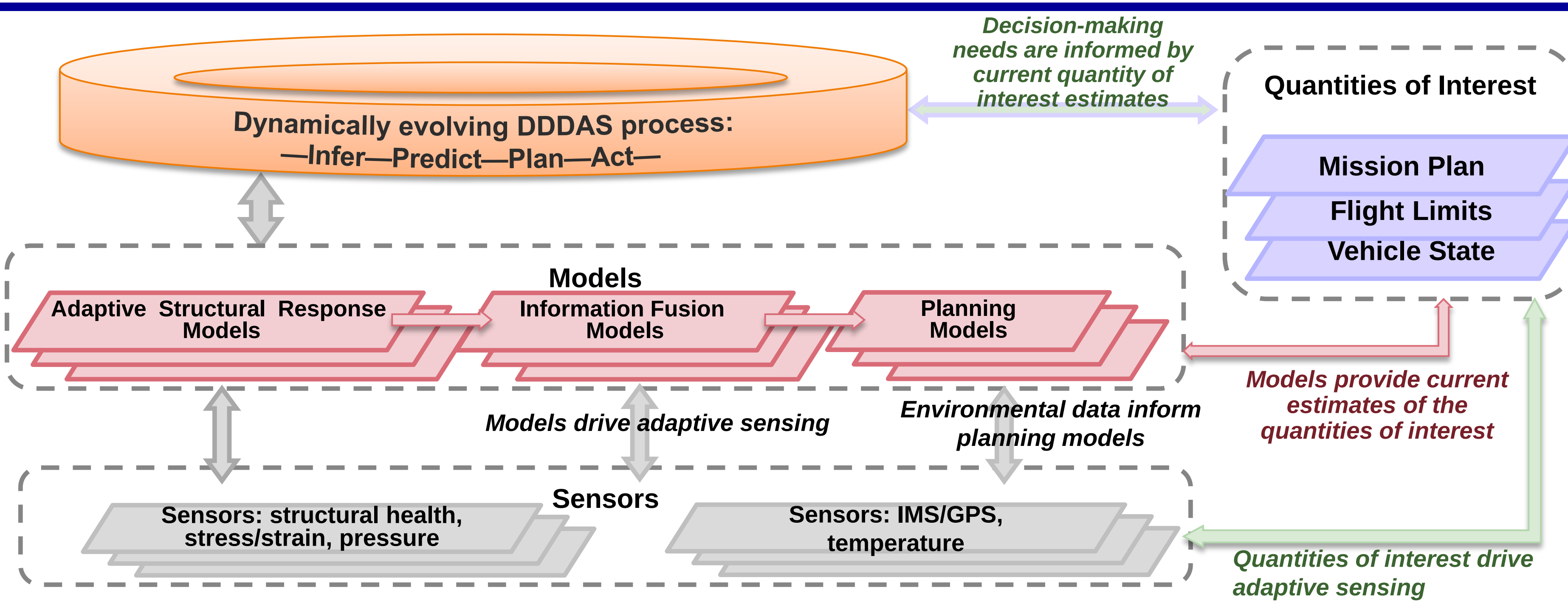
Leading to dynamic health-aware mission re-planning with quantifiable benefits in reliability, maneuverability and survivability.

Methodologies

- statistical inference for dynamic vehicle state estimation, using machine learning and reduced-order modeling
- adaptive reduced-order models for vehicle flight limit prediction using dynamic data
- on-line management of multi-fidelity models and sensor data, using variance-based sensitivity analysis
- quantify the reliability, maneuverability and survivability benefits of a self-aware UAV

Dynamic Data-Driven Methods for Self-Aware Aerospace Vehicles

D Allaire, L Mainini, F Ulker, M Lecerf, H Li, K Willcox (MIT); G Biros, O Ghattas (UT Austin); J Chambers, R Cowlagi, D Kordonowy (Aurora)



INFERENCE

- Confident estimation of vehicle state in offline phase, time-sensitive estimation of vehicle state in online phase
- Onboard damage model updated using sensed structural data/state
- Efficient algorithms scale well on GPU and manycore architectures

PREDICTION

- Update estimates of flight limits via adaptive reduced-order models
- Progressively fuse higher fidelity information with current information as more time and resources become available
- Sensitivity analysis for dynamic online management of multifidelity models & sensors for vehicle state & flight limit

PLANNING

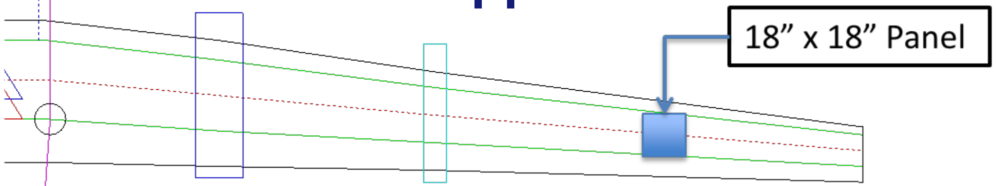
- Dynamic environmental data inform online adaption of reduced-order models for mission planning
- Multifidelity planning approaches using reduced-order models
- Quantification of reliability, maneuverability, survivability

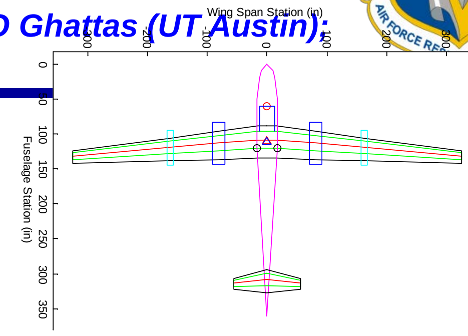
Dynamic Data-Driven Methods for Self-Aware Aerospace Vehicles

D Allaire, L Mainini, F Ulker, M Lecerf, H Li, K Willcox (MIT); G Biros, O Ghattas (UT Austin); J Chambers, R Cowlagi, D Kordonowy (Aurora)

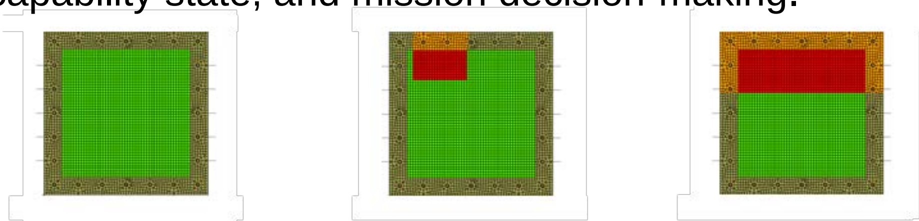
An offline/online DDDAS approach

- **Test case: composite panel on a UAV**





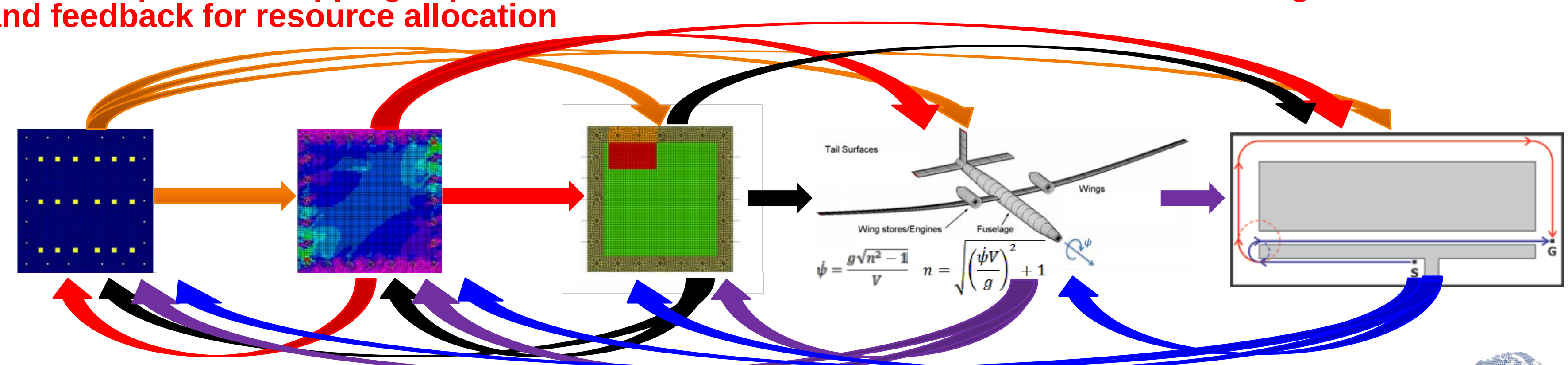
- **Offline**: develop libraries of panel strain information, under different load/damage scenarios under uncertainty. Develop data-driven reduced-order models to map from sensed strain to damage state, capability state, and mission decision-making.



Example damage scenarios caused by ply delamination. Red and orange indicate delamination sites.

- **Online**: information management strategy for dynamic sensor and model-based data acquisition, damage and capability state updates, and dynamic mission re-planning.

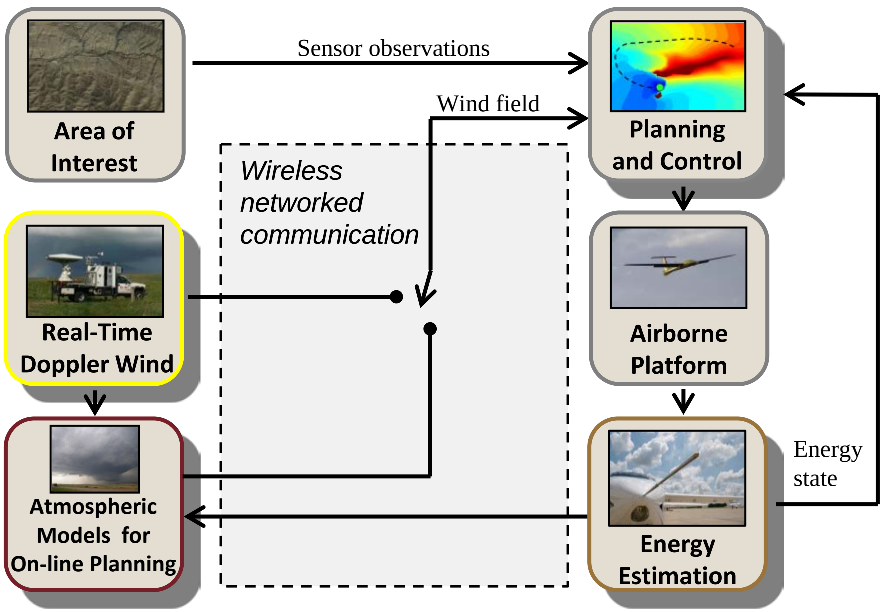
Arrows represent mapping capabilities from sensor data to mission decision-making, and feedback for resource allocation



Sensor information | **Strain field estimation** | **Damage state estimation** | **Capability state estimation** | **Mission decision-making**

Energy-Aware Aerial Systems for Persistent Sampling and Surveillance

E. W. Frew, Brian Argrow- U of Colorado-Boulder; Adam Houston – U of Nebraska-Lincoln)
Chris Weiss - Texas Tech University



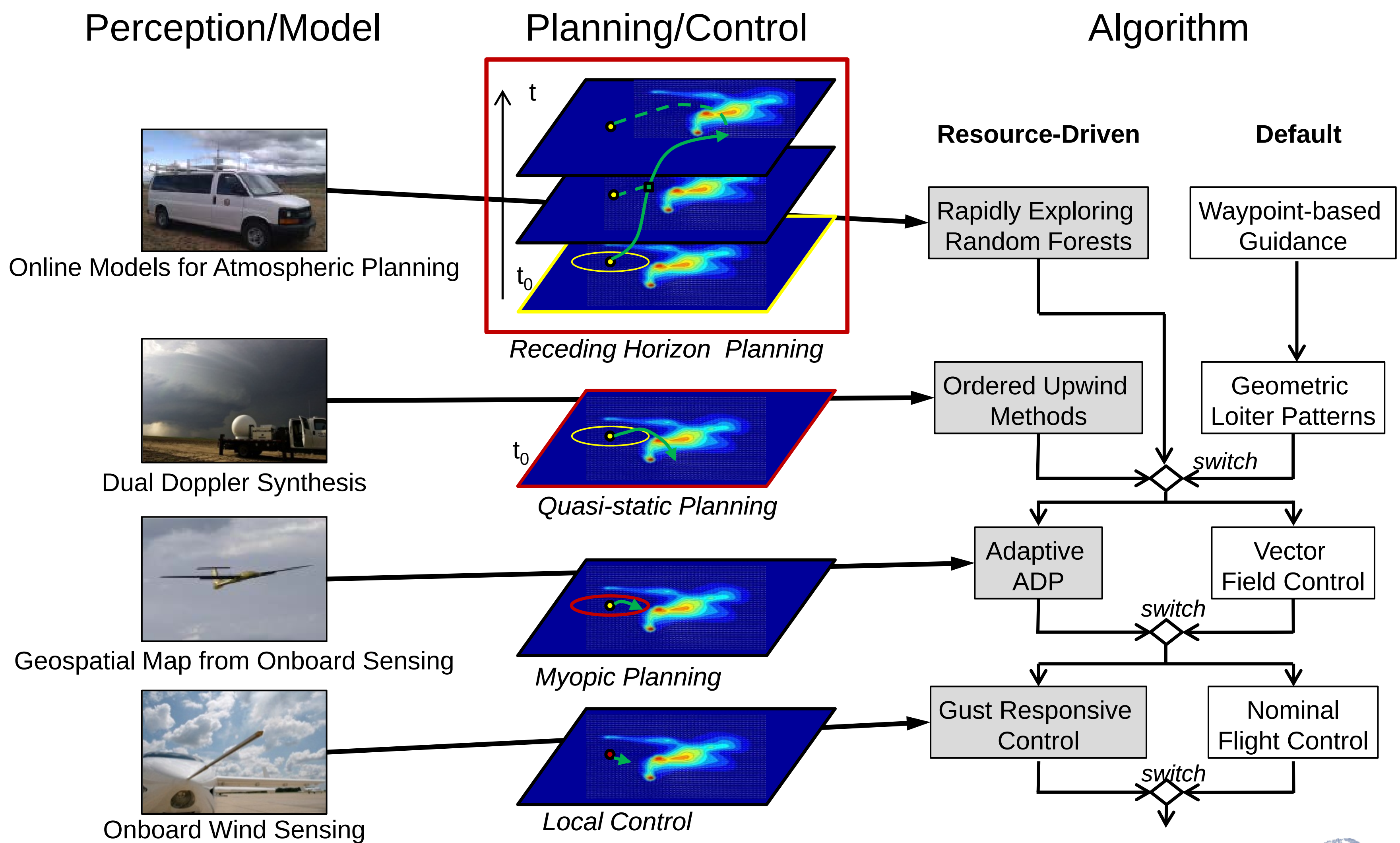
This effort will develop, assess, and deliver new Air Force capabilities in the form of energy-aware, airborne, dynamic data-driven application systems (EA-DDDAS) that can perform persistent sampling and surveillance in complex atmospheric conditions.

Features of the EA-DDDAS span the four key DDDAS technology frontiers

- Decision-making over different **application modeling layers** that include
  - local aircraft energy and wind states
  - spatio-temporal wind fields
  - dual-Doppler synthesis of regional winds
  - on-line models for atmospheric planning.
- **Mathematical algorithms** that provide high degree of autonomy with control loops closed over multiple spatial and temporal scales.
- New **measurement systems and methods** whereby disparate information sources are assimilated by online models; mobile sensors are targeted to relevant measurements in real time; and data processing rates are throttled in response to computation resource availability.
- Net-centric middleware **systems software** that connects multiple systems with computation and control resources dispersed over wireless communication networks.

Energy-Aware Aerial Systems for Persistent Sampling and Surveillance

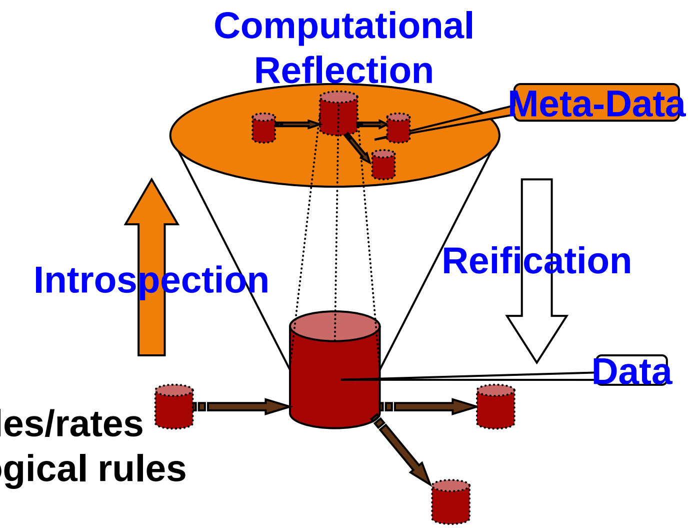
E. W. Frew, Brian Argrow- U of Colorado-Boulder; Adam Houston – U of Nebraska-Lincoln)
Chris Weiss - Texas Tech University



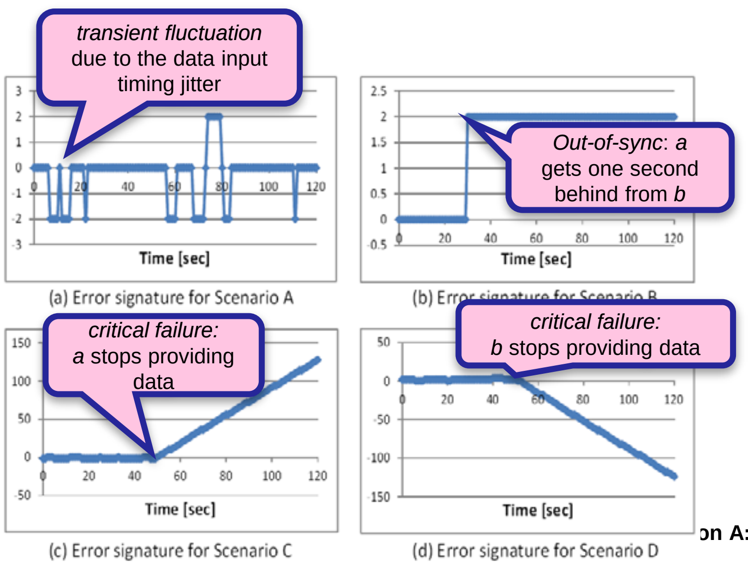
Stochastic Logical Reasoning for Autonomous Mission Planning

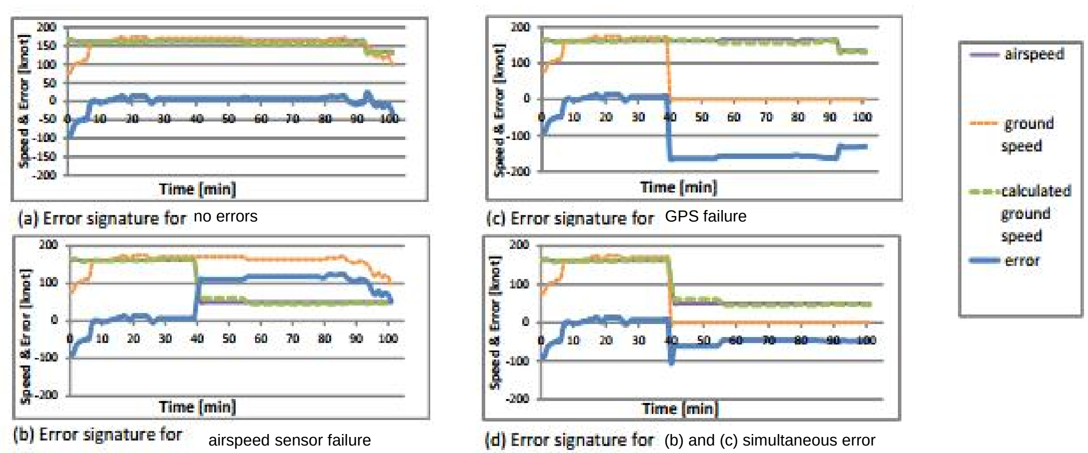
Carlos A. Varela - Worldwide Computing Laboratory, Computer Sciences, RPI

- **Project Objectives:**
  - **develop dynamic data-driven computational model: *active data*; application to autonomous mission planning**
    - autonomously act upon changes in data sources to maintain itself continuously up to date;
    - semi-automatically discover knowledge derivable from data



- **Project Scope and Approach:**
  - **general aviation flight planning as driving scenario**
  - **active data spatial/temporal information streams at different scales/rates**
  - **data relationships from mathematical formulae and stochastic logical rules**
  - **develop a quantitative spatial and temporal logic**
  - **investigate extensions to logic programming to support stochastic reasoning**
  - **Example Case: Avoidance of Pitot-Tube failure**

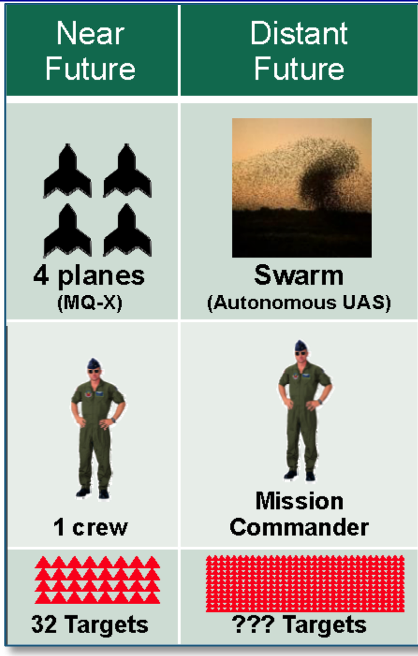




Application of DDDAS Principles to Command, Control and Mission Planning for UAV Swarms

M.B. Blake, G. Madey, C. Poellabauer – U. Of Notre Dame

Advancing ISR Capabilities: Intelligence, Surveillance, Reconnaissance, Situational Awareness, Wide Area Airborne Surveillance
Heterogeneity: Micro and Nano-sized Vehicles, Medium "fighter sized" Vehicles, Large "tanker sized" Vehicles, and Special Vehicles with Unique Capabilities
Complex UAV Missions: Cooperative Sensing(HUMINT; SIGINT), Mixed Platforms/Capabilities; Cooperate with other aircraft, ground resources, heterogeneous mix of UAVs
Complex Systems Support: Dynamic Adaptive Workflows; Adaptive Sensing, Computation, Communications



Maj. Gen. Hansen, 2009

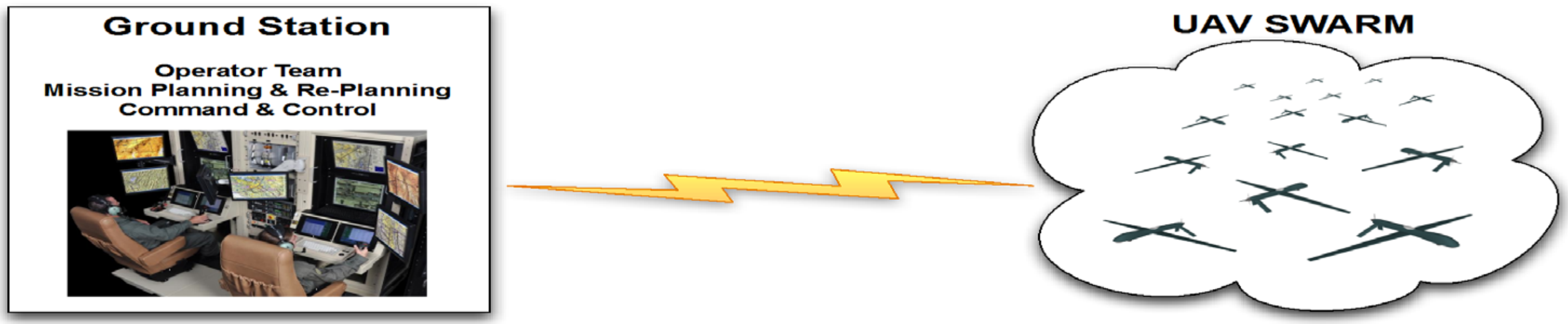
Increasing Operator Load – pilot and sensor operators may need to control "the swarm" not just one UAV
More Complex Missions –**Dynamic Mission Re-Planning –** surveillance, search & rescue, damage assessment
Resource Constraints – bandwidth, storage, processing, and energy

DDDAS Simulation Test-bed

AFRL UAV Swarm Simulator – Dynamic Data Source
Agent-Based DDDAS Simulation – Dynamically Updated Application
Dynamic Adaptive Workflow – DDDAS System Software
Mission Performance – Global & Local Metrics Optimization

Application of DDDAS Principles to Command, Control and Mission Planning for UAV Swarms

M.B. Blake, G. Madey, C. Poellabauer – U. Of Notre Dame



Application of DDDAS Principles to Command, Control and Mission Planning for UAV Swarms
Research Test-Bed

Agent-Based Simulator
Java/RePast/MASON

Abstract Simulation of Air Vehicles, Interaction with Environment and other Vehicles, and other Agents

Dynamically Updated Application

DDDAS Simulation of UAV Swarm

Control Parameters →

System Software QoS Service Composition

← Real-Time Sensor Feedback

UAV Swarm Simulator
MultiUAV2 - AFRL/RBCA

6DOF Simulation of Air Vehicles Tactical Maneuvering, Sensor, Target, Cooperation, Route, and Weapons

Sensor & Air Vehicle Performance

Synthetic UAV Swarm

How to ensure correctness and consistency in simulation that is dynamically updated?

Challenges / Possible Solutions

How to ensure correctness and completeness of dynamically updated workflows?

Atomic execution/rollbacks? Deadlock detection? Two phase commits? Checkin/checkout? Parallel execution paths?

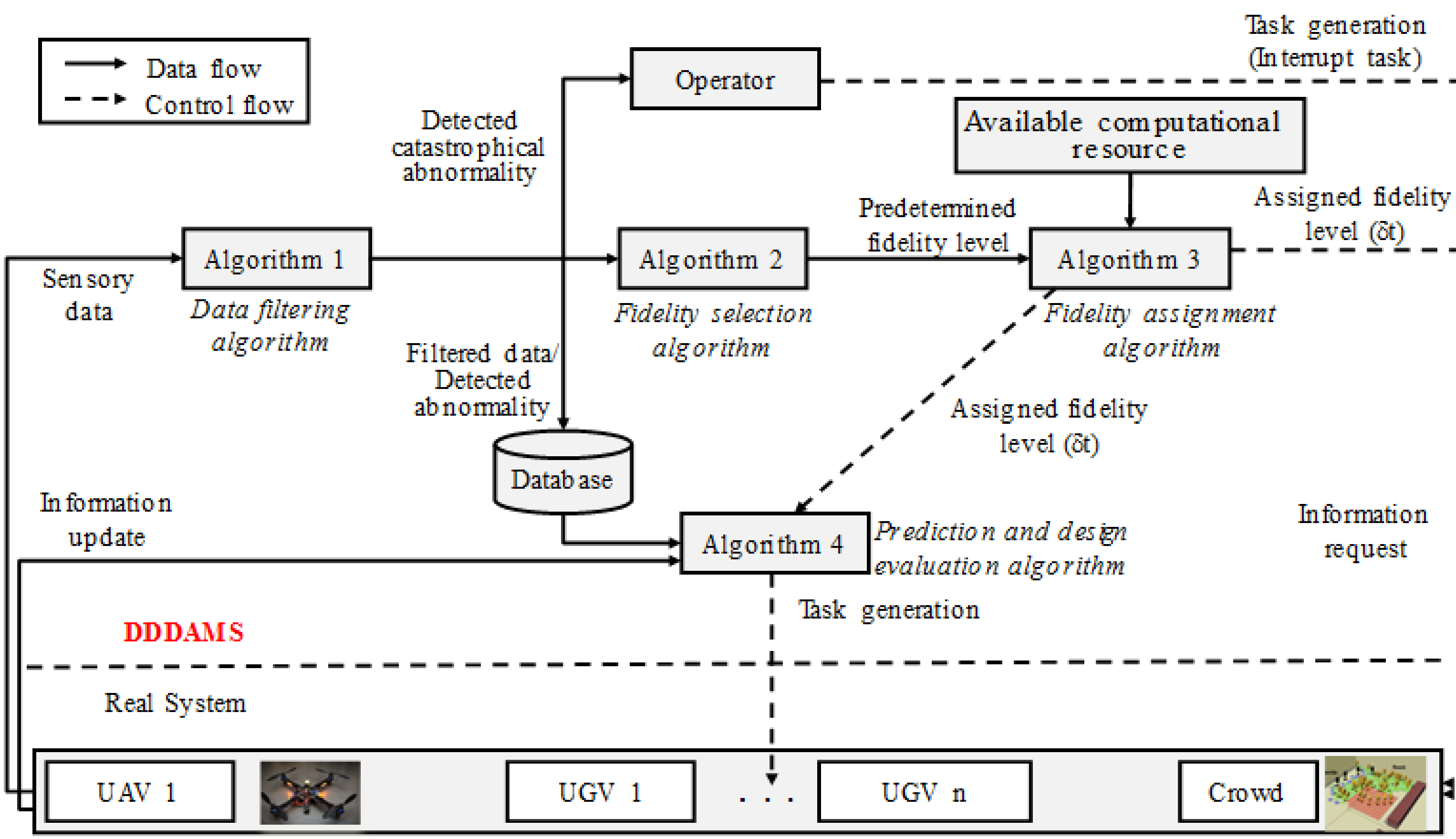
Project Highlights of Work To Date

- **Modular test-bed to support Swarm Task Assignment For Mission Planning**
- **Simulating Multi-hop Communications in a Swarm of UAVs to support UAV Cooperative Search**
- **UAV Mission Vessel Tracking to support Flying the Swarm Rather than the UAVs**

DDDAMS-based Urban Surveillance and Crowd Control via UAVs and UGVs

Young-Jun Son, Jian Liu, University of Arizona; Jyh-Ming Lien, Computer Science, George Mason University

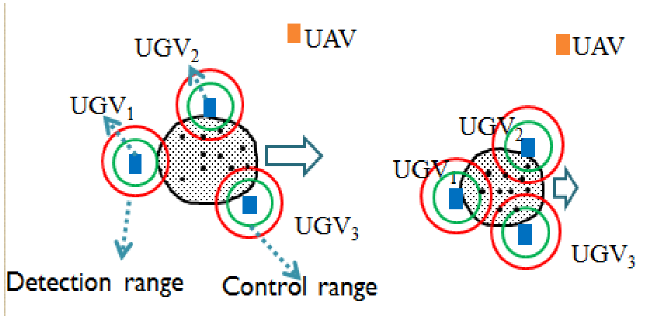
- **Goal: To create scalable, robust, multi-scale, and effective urban surveillance and crowd control strategies using UAVs and UGV**
- **Approach: Comprehensive planning and control framework based on dynamic data-driven, adaptive multi-scale simulation (DDDAMS)**



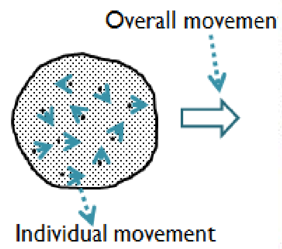
Young-Jun Son, Jian Liu, University of Arizona; Jyh-Ming Lien, Computer Science, George Mason University

Approach: Detailed Methods (1)

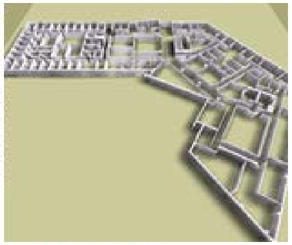
- **Task 1: Development of algorithms to improve performance of coordinated UAV and UGVs in tracking and controlling human crowd**
- **More detailed scenario**
  - **Role of UAV/UGV: detect, track, and control crowd**
  - **Performance of crowd control: probability of targets in crowd under control coverage (quantified by control range)**
  - **Crowd movement: both individual and overall movement**
- **Detailed methods enabling DDDAMS**
  - **Bayesian-based information aggregation/disaggregation among UAV and UGV**
  - **Dynamic information updating based on observation/simulation**
  - **Temporal and spatial data fusion for enhanced performance**
  - **Multi-resolution strategy in temporal tracking frequency**
  - **Cached intelligent observers (CIO) for following a group in a complex environment**



time t time $t+1$



A virtual city with 161 buildings



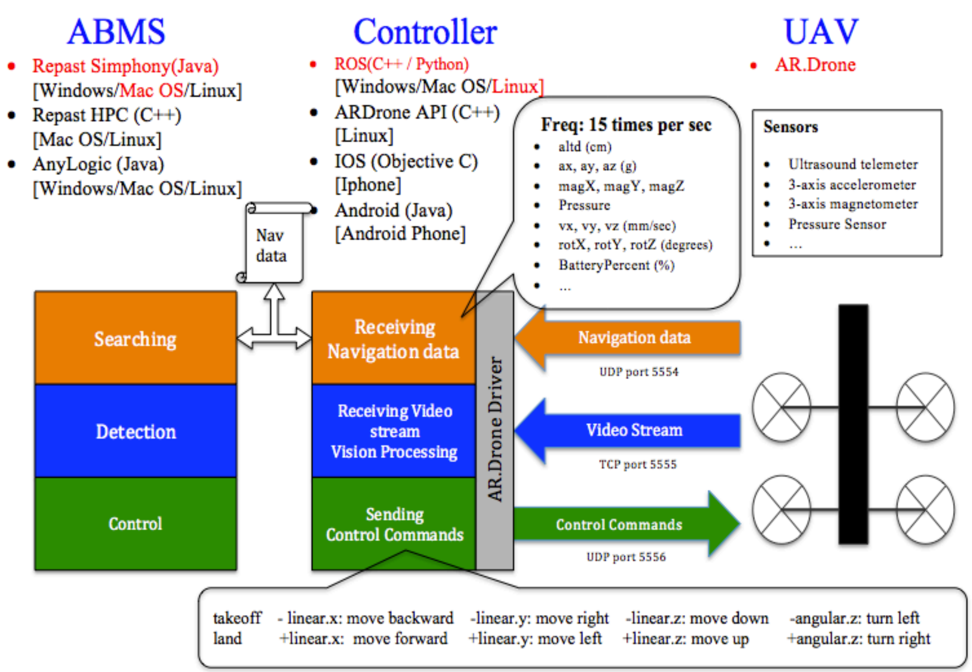
2nd Floor GMU Engineering Building 81 rooms

DDDAMS-based Urban Surveillance and Crowd Control via UAVs and UGVs

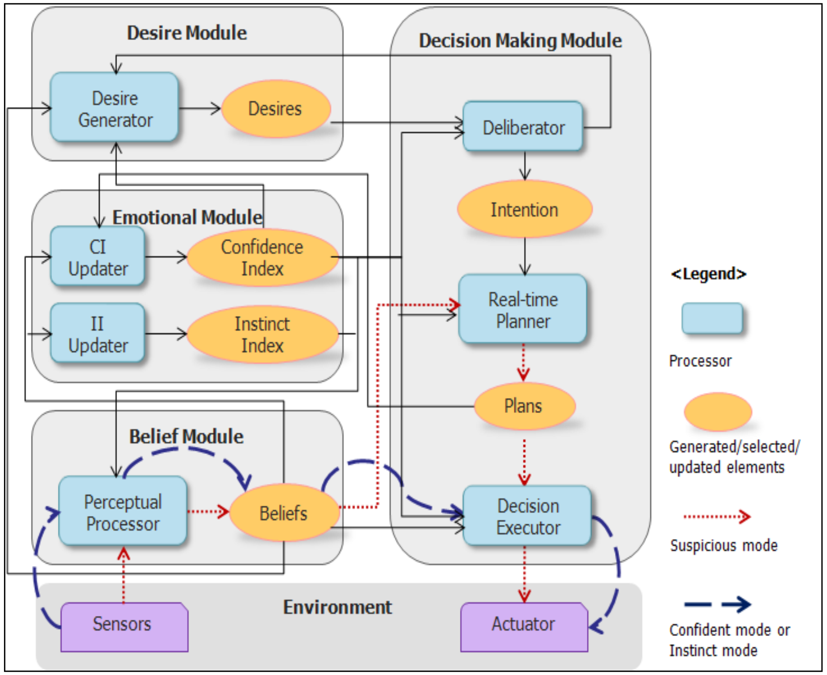
Young-Jun Son, Jian Liu, University of Arizona; Jyh-Ming Lien, Computer Science, George Mason University

Approach: Detailed Methods (2)

- **Task 2: Development of a hardware-in-the-loop simulation/control framework and testbed for crowd control**
- **Detailed methods enabling DDDAMS**
  - **Agent-based modeling and simulation (ABMS); real-time simulation**
  - **(future task) Crowd behavior based on Belief-Desire-Intention (BDI) model**
  - **(future taks) Implementation of computer vision algorithms using Matlab/OpenCV**



Proposed HIL Simulation Framework

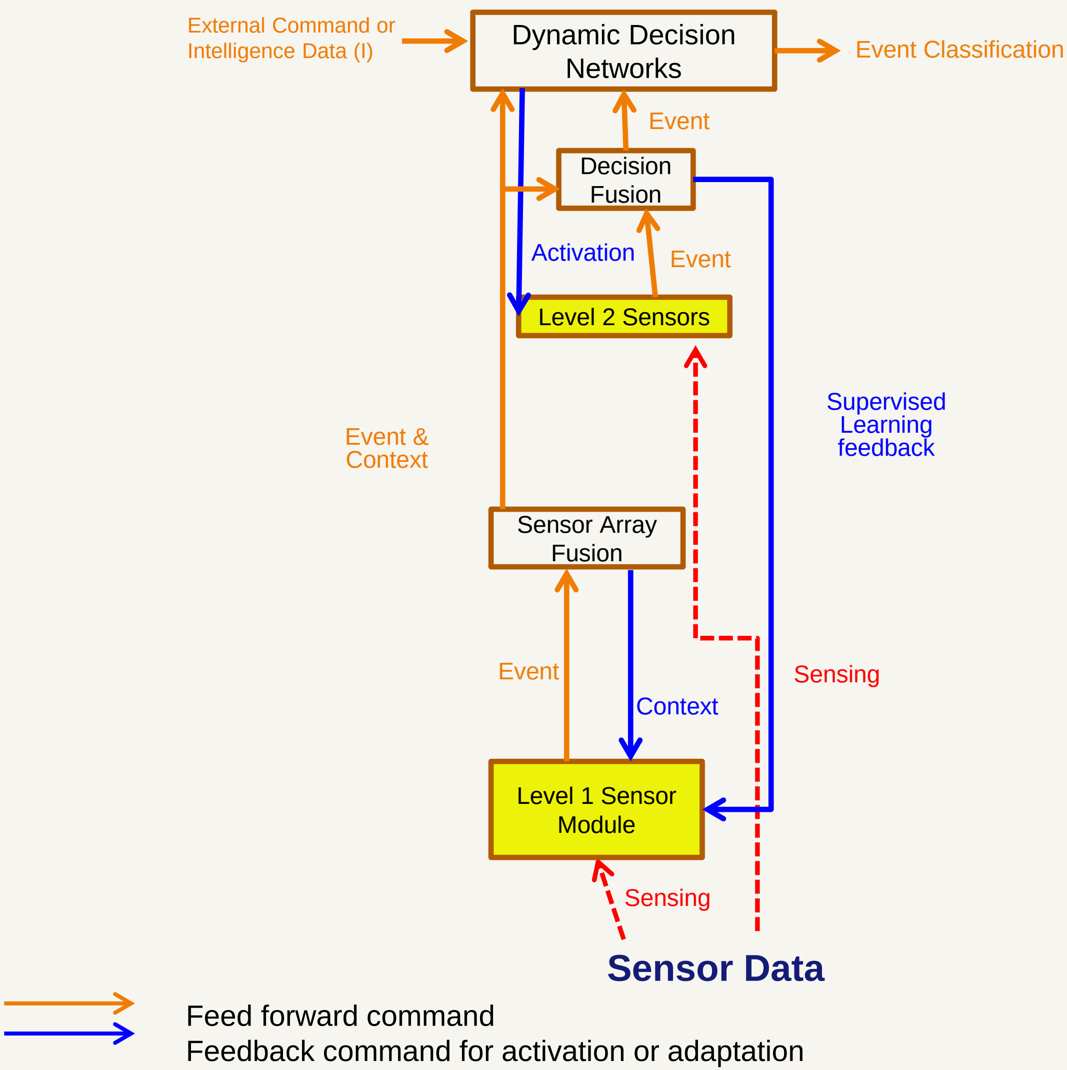


Extended BDI model for human

Dynamic Data Driven Adaptation via Embedded Software Agents for Border Control Scenario

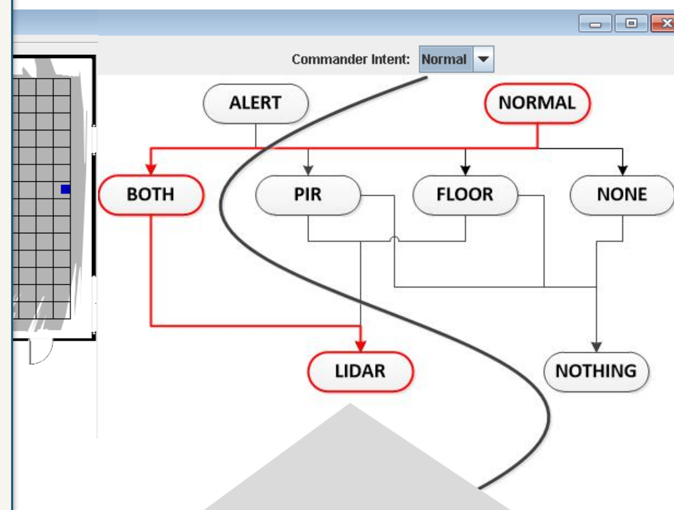
Shashi Phoha, Doina Bein, Penn State

DDDAS Loop



ı and dynamic decisions networks for a
tem consisting of ground & airborne
actions for improving target identification.
nproving the classification performance of
m higher level.
sions based on the contextual information

isplays what sensors become active when human is detected



ra (UAV)

twork

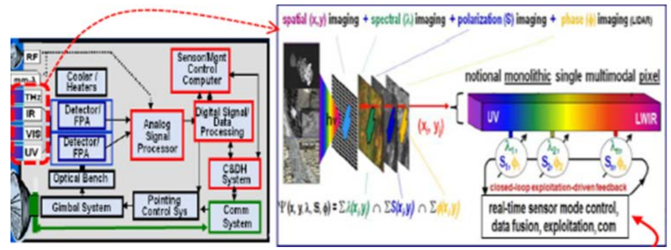
Aerial picture taken when human is detected

Multiscale Analysis of Multimodal Imagery for Cooperative Sensing

AFOSR LRIR – *Erik Blasch, Guna Seetharaman, RI Directorate, AFRL*

Multi-scale Multimodal Data

Full Motion Video



Sensor Management

Theory

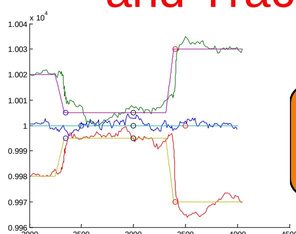
$$\varepsilon_{t+\Delta t} = \varepsilon_t \, e^{\lambda(\varepsilon t)\Delta t}$$

Object ID and Tracking

Filtering

User Refinement

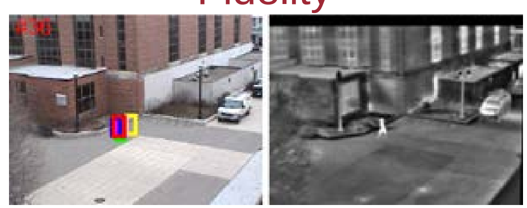
Modeling



Simulations

Mission Management

Operational Condition Fidelity



Members of U.S. Joint Forces Command's Joint Intelligence Laboratory monitor data from sites participating in Empire Challenge 2009. U.S. DEFENSE DEPARTMENT

Measurements

Situation Assessment

Forecasting, Prediction

DDDAS for Object Tracking in Complex and Dynamic Environments (DOTCODE)

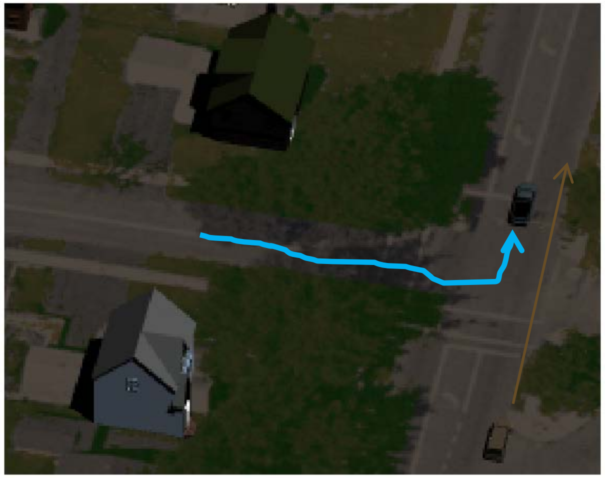
Anthony Vodacek , John Kerekes, Matthew Hoffman (RPI)

- Create capabilities to ***enhance remote object tracking*** *in difficult imaging situations where single imaging modality is in general insufficient*

- **Approach and objectives**
  - *Use the DDDAS concept of model feedback to the sensor which then adapts the sensing modality*
  - *Employ an adaptive multi-modal sensor in a simulation study*

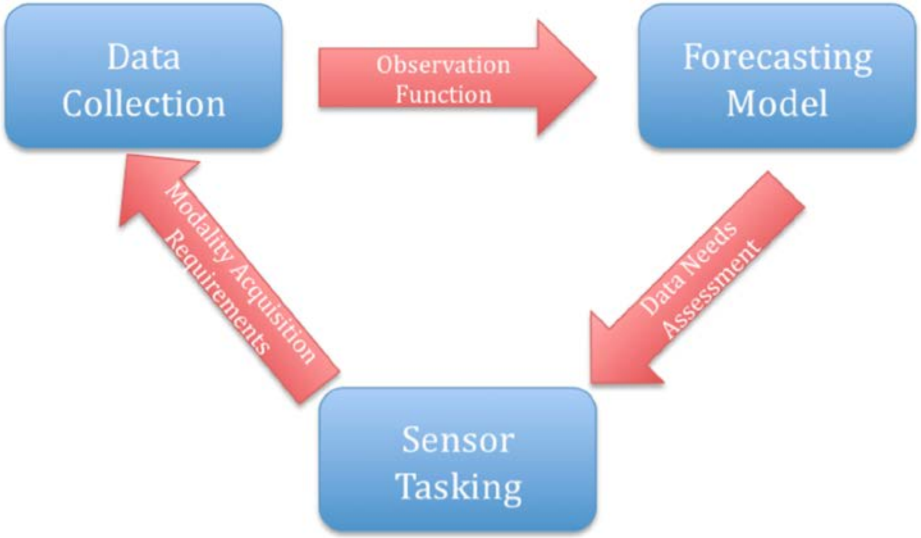
- **Methodology**
  - Simulation study will leverage existing high spatial resolution Digital Imaging and Remote Sensing Image Generation (DIRSIG) scenes of a cluttered urban area and a desert industrial complex

Road intersections from Open Street Map Registered to image

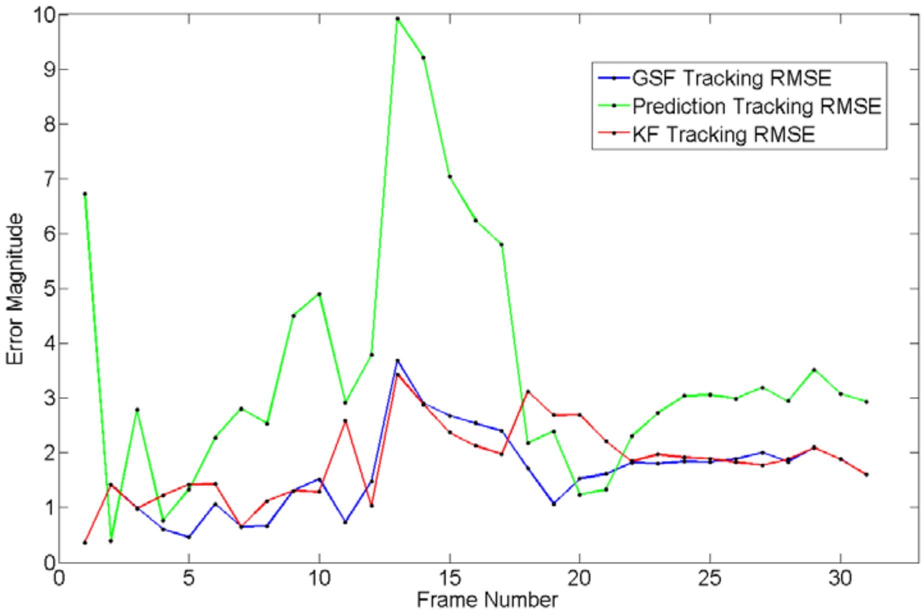


DIRSIG scene with moving vehicles

DDDAS cycle



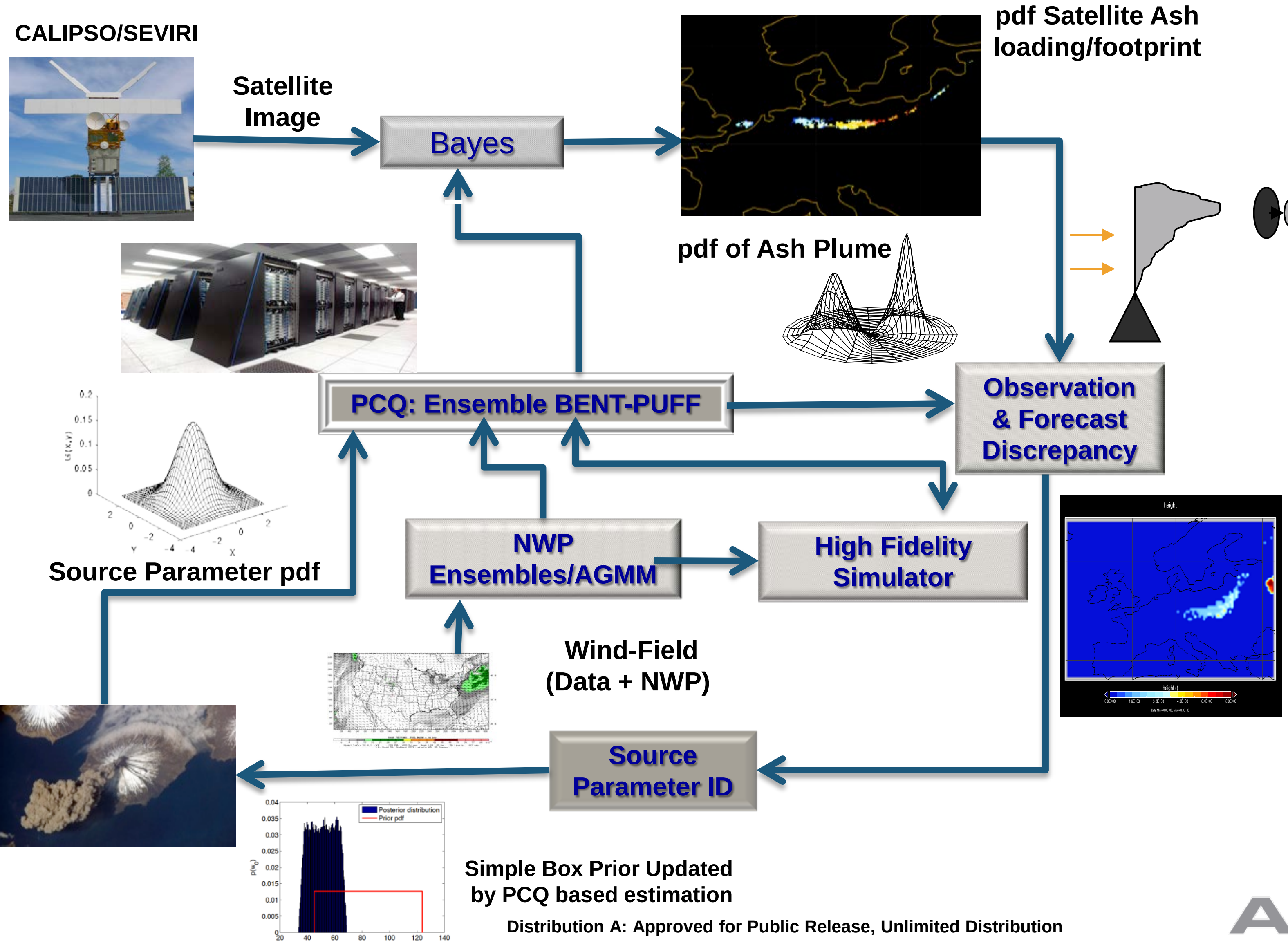
- **Research will leverage existing DIRSIG capability to model adaptive multimodal sensors (panchromatic and HSI or polarization and HIS)**
- **DIRSIG animations of moving objects**
- **Object tracking using particle filter approach – uses Gaussian Sum Filter – advantage to GSM observed for turning vehicle**
- **Developing adaptive image processing routines on both the targets and the background**
  - **Adaptive sampling schemes are being tested**
  - **Leverages Open Street Map for understanding the road network**



Gaussian Sum Filter has best performance

DDDAS Approach To Volcanic Ash Transport & Dispersal Forecast

A. Patra, M. Bursik, E. B. Pitman, P. Singla, T. Singh, M. Jones – Univ at Buffalo; M. Pavolonis Univ. Wisconsin/NOAA;
B. P. Webley, J. Dehn – Univ Alaska Fairbanks; A. Sandu Virginia Tech



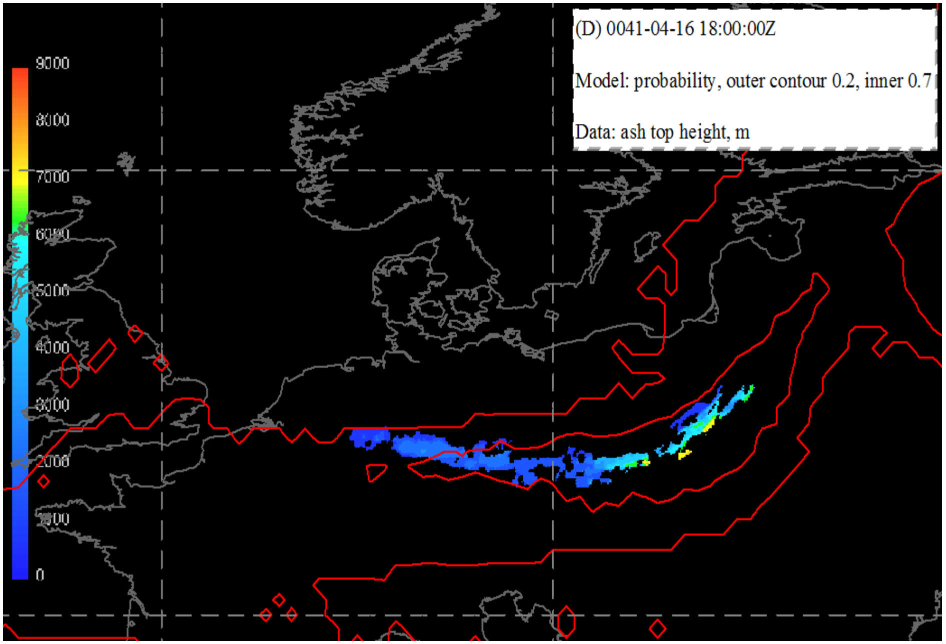
BENT: Eruption Plume Model
PUFF: Ash transport and Dispersal Model
PCQ: Polynomial Chaos Quadrature
NWP: Numerical Weather Prediction
AGMM: Adaptive Gaussian Mixtures
CALIPSO/SEVIRI: Satellite based sensors for ash detection

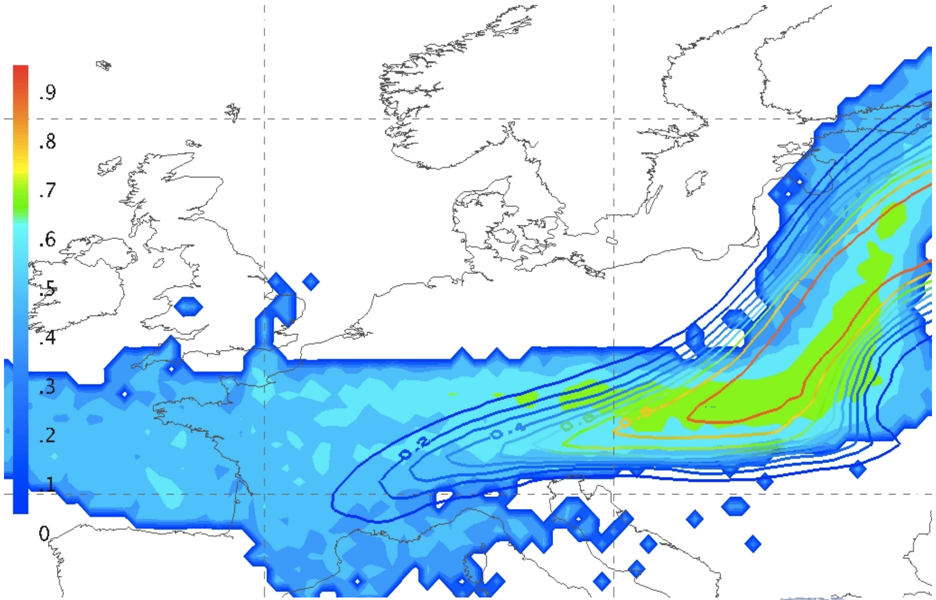
DDDAS Approach To Volcanic Ash Transport & Dispersal Forecast

A. Patra, M. Bursik, E. B. Pitman, P. Singla, T. Singh, M. Jones – Univ at Buffalo; M. Pavolonis Univ. Wisconsin/NOAA;
B. P. Webley, J. Dehn – Univ Alaska Fairbanks; A. Sandu Virginia Tech

Interim Progress:

- **Developed parallelized PCQ/Bent-Puff/ HPC based tool for probabilistic ash forecasting**
- **Physics based methodology for VATD "transport and dispersion" model inputs –**
  poorly characterized column height, mass eruption rate replaced by pdf of observable vent parameters and speed.
- **PCQ based probabilistic hazard analysis replaces deterministic predictions of existing tools. WRF ensembles used for incorporating effect of wind uncertainty**
- **Results for Eyjafjallojokull are very promising –**
  all ash observed was inside a Probability>0.2 contour with most in Probability >0.7
- **Presently, this is the only risk-based (probabilistic) forecast for ash cloud with full transport modeling**



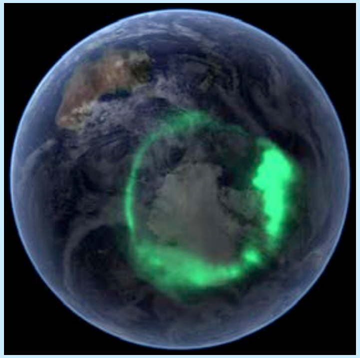


Transformative Advances in DDDAS with Application to Space Weather Modeling

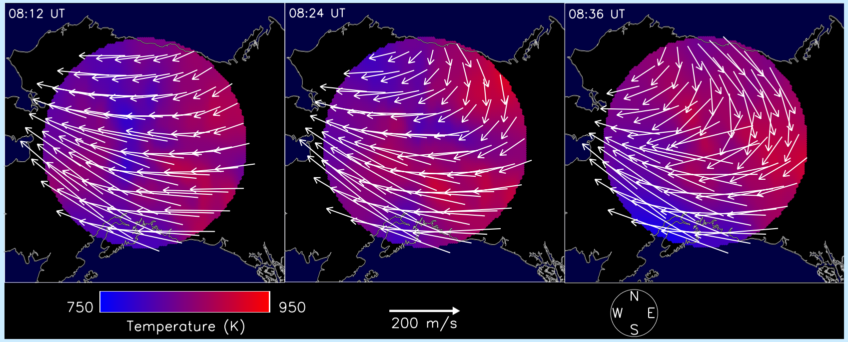
Dennis Bernstein (PI), Amy Cohn, James Cutler, Aaron Ridley – U of Michigan

- **Scientific Motivation**
  - **Unknown changes to the atmospheric density degrade the accuracy of GPS and impede the ability to track space objects**
- **Project Scope and Objectives**
  - **Apply DDDAS concepts and methods to space weather monitoring**
  - **Key goals are input estimation and model refinement to facilitate higher-accuracy data assimilation**
  - **Input reconstruction is used to estimate atmospheric drivers that determine the evolution of the ionosphere-thermosphere**
  - **Model refinement is used to improve the accuracy of atmospheric models**
  - **DDDAS supported by space physics modeling and mission planning and analysis**

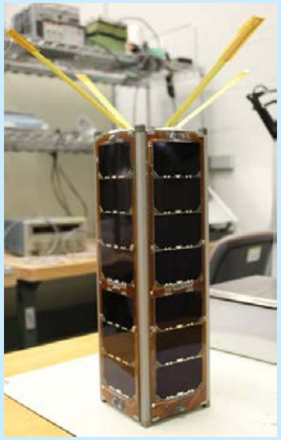
Space Debris



Auroral Heating



Wind Field Estimation



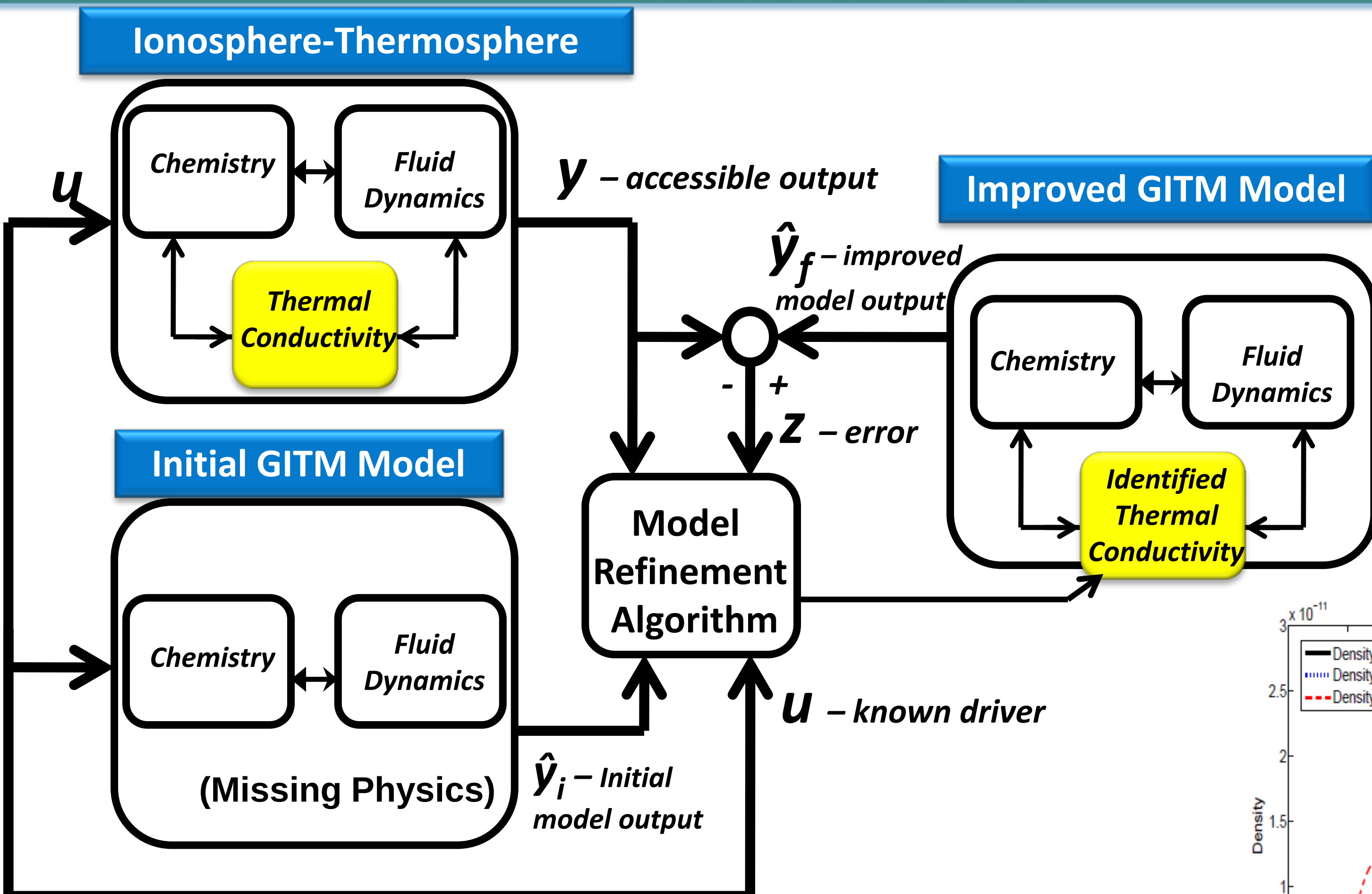
RAX-2 CubeSat

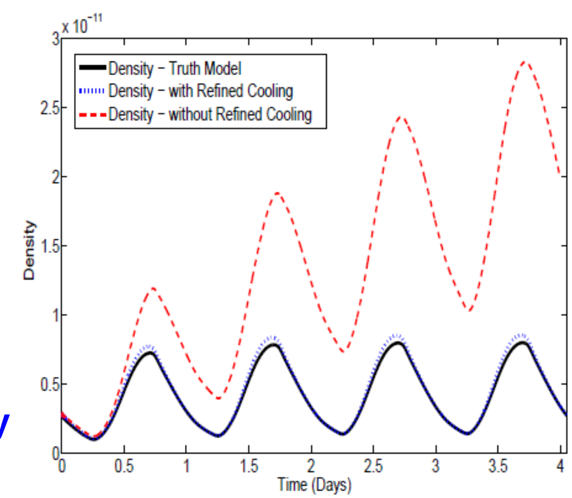
Transformative Advances in DDDAS with Application to Space Weather Modeling

Dennis Bernstein (PI), Amy Cohn, James Cutler, Aaron Ridley – U of Michigan

DDDAS Approach: *Model Refinement to Enable Enhanced Data Assimilation*

{GITM- Global I-T Model}





Example Case: Dynamic estimation of nitrous-oxide density (using NO cooling with the Improved GITM)

Portfolio of DDDAS Funded Projects

Projects (FY11 and FY12) included in this presentation (* - presented also in 2011 AFOSR Spring Review)

- ❖ Computational Steering of Large-Scale Structural Systems Through Advanced Simulation, Optimization, and
- ❖ Structural Health Monitoring
- ❖ Dynamic Data-Driven Methods for Self-Aware Aerospace Vehicles
- Energy-Aware Aerial Systems for Persistent Sampling and Surveillance
- Stochastic Logical Reasoning for Autonomous Mission Planning
- ❖ Application of DDDAS Principles to Command, Control and Mission Planning for UAV Swarms
- DDDAMS-based Urban Surveillance and Crowd Control via UAVs and UGVs
- Dynamic Data Driven Adaptation via Embedded Software Agents for Border Control Scenario
- ❖ Multiscale Analysis of Multimodal Imagery for Cooperative Sensing (LRIR – Labtask)
  DDDAS for Object Tracking in Complex and Dynamic Environments (DOTCODE)
- ❖ Application of DDDAS Ideas to the Computation of Volcanic Plume Transport
- Transformative Advances in DDDAS with Application to Space Weather Monitoring

Additional Projects (FY11 and FY12) supported under the DDDAS Program

- ❖ Development of a Stochastic Dynamic Data-Driven System for Prediction of Materials Damage
- Developing Data-Driven Protocols to study Complex Systems: The case of Engineered Granular Crystals (EGC)
- Dynamic Data-Driven Modeling of Uncertainties and 3D Effects of Porous Shape Memory Alloys
- Bayesian Computational Sensor Networks for Aircraft Structural Health Monitoring
- Fluid SLAM and the Robotic Reconstruction of Localized Atmospheric Phenomena
- Framework for Quantifying and Reducing Uncertainty in InfoSymbiotic Systems Arising in Atmospheric Environments
- Adaptive Stream Mining: A Novel Dynamic Computing Paradigm for Knowledge Extraction
- PREDICT: Privacy and Security Enhancing Dynamic Information Collection and Monitoring
- An Adaptive Property-Aware HW/SW Framework for DDDAS
- DDDAS-based Resilient Cyberspace (DRCS)
- New Globally Convex Models for Vision Problems using Variational Methods (LRIR)
- Symbiotic Partnership between Ground Observers and Overhead Image Analysis (LRIR)
- DDDAMS-based Real-time Assessment and Control of Air Force Base Microgrids - YIP

A dozen new projects expected to start in FY13

Other Program Interactions & Outreach

Publications by DDDAS PIs: over 80 (Journals, Conferences, Books)

Presentations by PIs: over 50 talks (Conf's, Seminars in Academe, Industry, Gov Agencies/Labs)

PIs Recognized with Awards

- ASME Award (Bazilevs); AFRL Research and Technology Award (Blasch, Seetharaman)

Interactions with AFRL Technical Directorates

- The Program has started engaging AFRL researchers – recently launched 3 new Lab Tasks

Transition Activities

- Volcanic Ash Propagation Modeling – adopted/Alaska
- Adaptive Stream Mining Systems (PI: Bhattacharya) – the classification-aware compression and remote mining approaches - evaluated by Cisco Systems Inc., for possible productization
- Multi-UAV Agent-Based Simulation (PI: Madey) - interactions with AFRL/RB) and AFIT
- DOTCODE (PI: Vodacek) - coordination with AFSOR- funded project

Workshop/PI-Meeting (Yearly)

- DDDAS Workshop in conjunction with ICCS (conference) – June2012; next DDDAS/ICCS meeting - June 2013
- www.dddas.org ; Other DDDAS Workshops(planned): DDDAS/ICCS2014; 2014 American Control Conference

Invited Presentations (examples)

- (Keynote) "From Big Data to New Capabilities" : NSF Workshop on *Big Data from Signal Processing*, March 2013; AIE Symposium on Big Data, Dec, 2013; NSF *CyberBridges* Workshop, June , 2012
- (Keynote) "InfoSymbiotics – The Power of Dynamic Data Driven Applications Systems (DDDAS)", 5th *Symposium on Integrating CFD and Experiments in Aerodynamics* ("Integration"), Tokyo-Japan, Oct 3-5, 2012
- (Keynote) New Frontiers through Computer and Information Science; International Conference on Computational Science, June 2012
- (Panelist) "Five Thematic Areas for New Fundamental Capabilities for Dynamic Complex Systems", *National Security Symposium,* April 2012; "From Big Data to New Capabilities" NIST *BIG DATA* Symposium, June 2012

Recognition

- IIT Professional Achievement Award (April 2013)

back-ups

Additional Projects (FY11 and FY12) supported under the DDDAS Program

(with Principal Investigator names/affiliations)

- **Development of a Stochastic Dynamic Data-Driven System for Prediction of Materials Damage**
  - ***PI: Tinsley Oden, UT Austin***
- **Developing Data-Driven Protocols to study Complex Systems: The case of Engineered Granular Crystals (EGC)**
  - ***PI: Yannis Kevrekidis, Princeton Univ***
- **Dynamic Data-Driven Modeling of Uncertainties and 3D Effects of Porous Shape Memory Alloys**
  - ***PI: Craig Douglas, U of Wyoming***
- **Bayesian Computational Sensor Networks for Aircraft Structural Health Monitoring**
  - ***PI: Thomas Henderson, U. of Utah***
- **Fluid SLAM and the Robotic Reconstruction of Localized Atmospheric Phenomena**
  - ***PI: Sai Ravela, MIT***
- **A Framework for Quantifying and Reducing Uncertainty in InfoSymbiotic Systems Arising in Atmospheric Environments**
  - ***PI: Adrian Sandu, Virginia Tech***
- **Adaptive Stream Mining: A Novel Dynamic Computing Paradigm for Knowledge Extraction**
  - ***PI: Shuvra Bhattacharyya, U,. Of Maryland***
- **PREDICT: Privacy and Security Enhancing Dynamic Information Collection and Monitoring**
  - ***PI: Vaidy Sunderam, Emory U.***
- **An Adaptive Property-Aware HW/SW Framework for DDDAS**
  - ***PI: Philip Jones, Iowa State U.***
- **DDDAS-based Resilient Cyberspace (DRCS)**
  - ***PI: Salim Hariri, Arizona State U. Tucson***
- **New Globally Convex Models for Vision Problems using Variational Methods (LRIR)**
  - ***PI: Guna Sheetharanam, AFRL-RI***
- **Symbiotic Partnership between Ground Observers and Overhead Image Analysis (LRIR)**
  - ***PI: Brian Tsou, AFRL-RH***
- **DDDAMS-based Real-time Assessment and Control of Air Force Base Microgrids – YIP**
  - ***PI: Nurcin Celik, U. of Maimi***

Impact of prior DDDAS Efforts – Multidisciplinary & NSF-led /Multiagency (Examples of Areas of DDDAS Impact)

- **Physical, Chemical, Biological, Engineering Systems**
  - Chemical pollution transport (atmosphere, aquatic, subsurface), ecological systems, molecular bionetworks, protein folding..
- **Medical and Health Systems**
  - MRI imaging, cancer treatment, seizure control
- **Environmental (prevention, mitigation, and response)**
  - Earthquakes, hurricanes, tornados, wildfires, floods, landslides, tsunamis, …
- **Critical Infrastructure systems**
  - Electric-powergrid …ms, water supply systems, tran… …works and vehicles (air, ground, underw…
  - … …syst…
  - Large-Scale Com… …onments

"revolutionary" concept enabling to design, build, manage and understand complex systems

NSF/ENG Blue Ribbon Panel (Report 2006 – Tinsley Oden)

"DDDAS … key concept in many of the objectives set in Technology Horizons"

Dr. Werner Dahm, (former/recent) AF Chief Scientist

List of Projects/Papers/Workshops in www.cise.nsf.gov/dddas, www.dddas.org

(+ recent/August2010 MultiAgency InfoSymbtiotics/DDDAS Workshop)

Unification across Multicore-based Systems (InfoGrids)

(Multicores everywhere!)

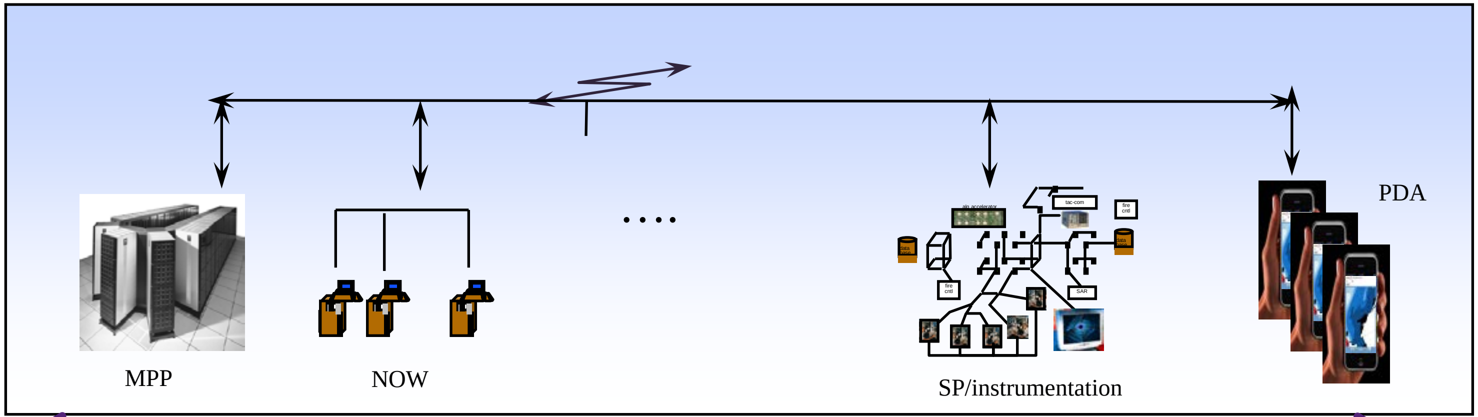
Multicores in High-End Platforms

- Multiple levels of hierarchies of processing nodes, memories, interconnects, latencies

Multicores in "measurement/data" Systems

- Instruments, Sensors, Controllers, Networks, …

Multiple levels of muticores



DDAS - Integrated/Unified Application Platforms

Adaptable Computing and Data Systems Infrastructure
spanning the high-end to real-time data-acquisition & control systems
manifesting heterogeneous multilevel distributed parallelism
system architectures – software architectures

Fundamental Research Challenges in Applications- and Systems-Software

- **Map the multilevel parallelism in applications to the platforms multilevel parallelism and for multi-level heterogeneity and dynamic resource availability**
- **Programming models and environments, new compiler/runtime technology for adaptive mapping**
- **Adaptively compositional software at all levels (applications/algorithms/ systems-software**
- **"performance-engineering" systems and their environments**

SuperGrids: Dynamically Coupled Networks of Data and Computations

DDDAS Approach to study Complex Systems Dynamics and Design:

The case of Engineered Granular Crystals (EGC)

Y. Kevrekidis – Princeton U.; Ch. Daraio – Caltech; P. Kevrekidis - UMass

Project Goals :

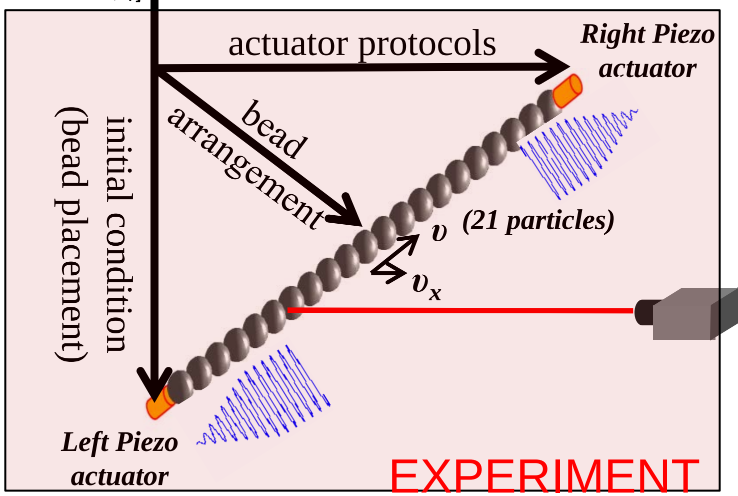
1. Dynamic acceleration of the experiments.

2. Dynamic optimization of EGC design.

3. Dynamic data mining to obtain coarse system observables.

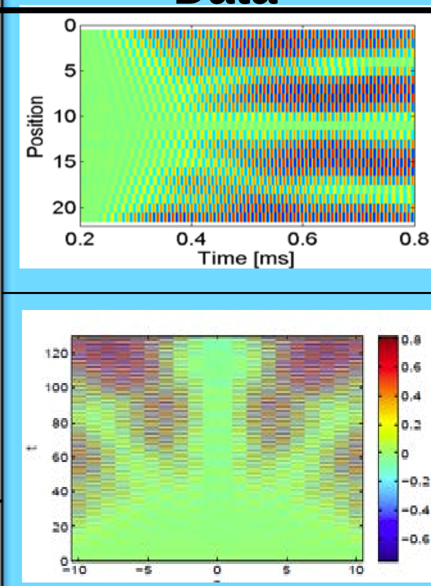
- Dynamic Data Driven experimental protocols
  - Design of initial EGC placements/ velocities
  - Design of EGC bead arrangement/type

DDD Design of



Dynamic Data mining: Diffusion maps

Data



<u>High fidelity simulations</u>

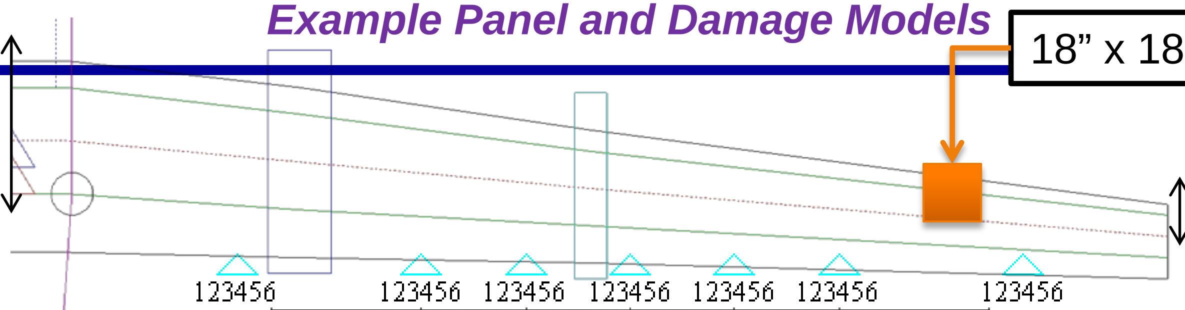
$$M\ddot{y}_n = V'_{\mathrm{FPU}}(y_{n+1}) - 2V'_{\mathrm{FPU}}(y_n) + V'_{\mathrm{FPU}}(y_{n-1}).$$

$$i\partial_T A(X,T) + \nu_2\partial_X^2 A(X,T) + \nu_3 A(X,T)|A(X,T)|^2 = 0.$$

Dynamic Data-Driven Methods for Self-Aware Aerospace Vehicles

D Allaire, L Mainini, F Ulker, M Lecerf, H Li, K Willcox (MIT); G Biros, O Ghattas (UT Austin); J Chambers, R Cowlagi, D Kordonowy (Aurora)

Example Panel and Damage Models

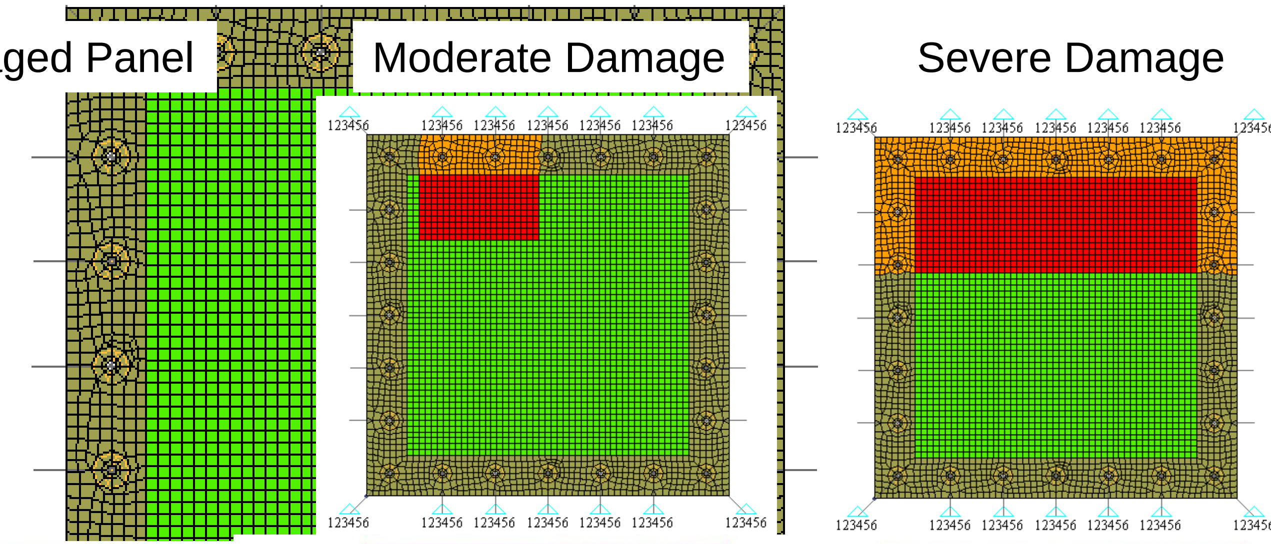


Undamaged Panel

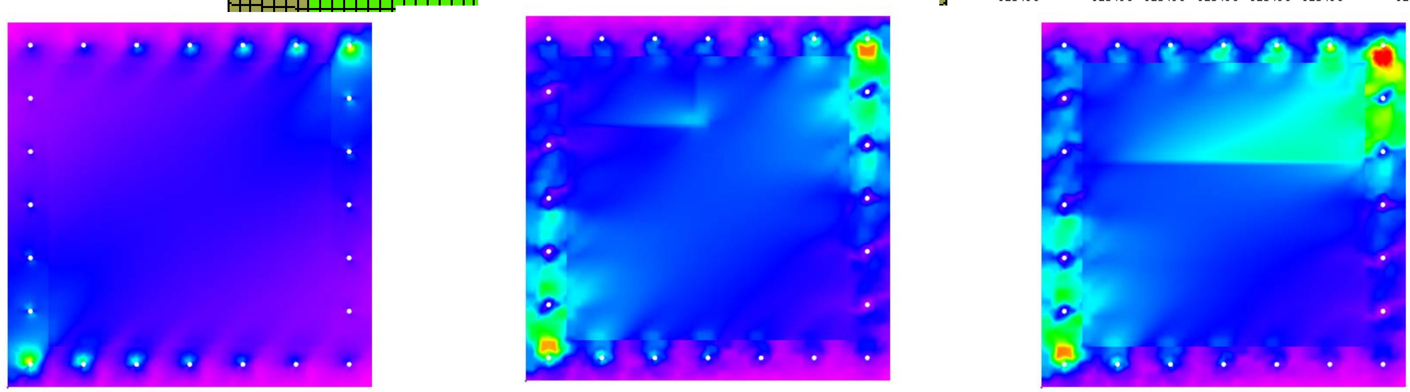
Moderate Damage

Severe Damage

Panel finite element model



Panel predicted strain after remeshing

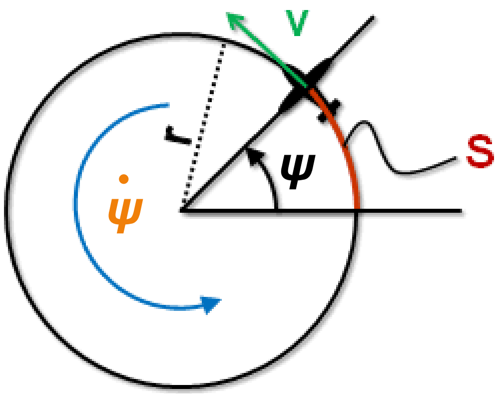


Dynamic Data-Driven Methods for Self-Aware Aerospace Vehicles

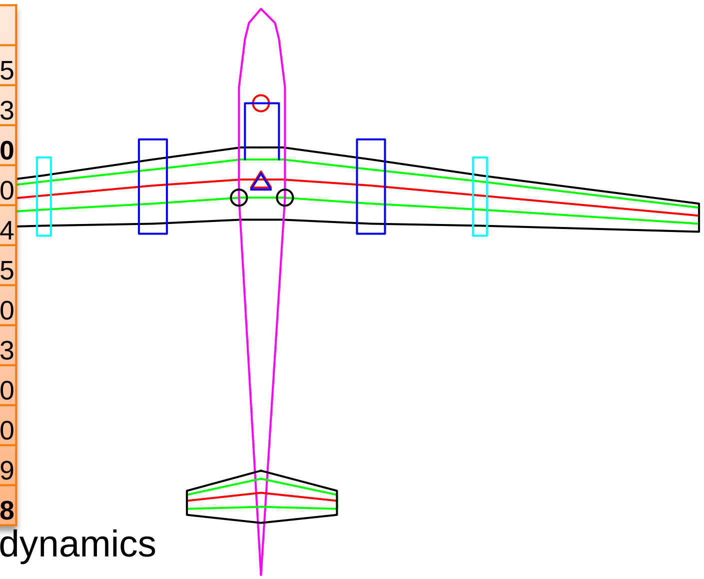
D Allaire, L Mainini, F Ulker, M Lecerf, H Li, K Willcox (MIT); G Biros, O Ghattas (UT Austin);
J Chambers, R Cowlagi, D Kordonowy (Aurora)

Baseline UAV & Vehicle Dynamics Models

Standard Rate Turn



Component	Weight (lbs)
Fuselage	660.5
Wing	335.3
Payload	**500.0**
Vertical Tail	42.0
Horizontal Tail	13.4
Engine	423.5
Pylon	50.0
Fuel	1,101.3
HPE System	450.0
Nose Landing Gear	36.0
Main Landing Gear	119.9
Sum	**3,811.8**



- Concept UAV with 500lb payload used to estimate vehicle dynamics
- Standard Rate (Sustained) Turn links vehicle structural capability to maneuverability performance
  - Turn rate equivalent to sustained load factor on wing lift loading

<u>*Turn Rate*</u>

$$\dot{\psi} = \frac{g\sqrt{n^2 - 1}}{V}$$

<u>*Turn Radius*</u>

$$r = \frac{V}{\dot{\psi}}$$

<u>*Load Factor*</u>

$$n = \sqrt{\left(\frac{\dot{\psi}V}{g}\right)^2 + 1}$$

  - Lift distribution along wings is reacted by wing box in bending and shear

$$\tau_{\text{web}} = \frac{\mathcal{S}_\perp(\eta)}{A_{\text{web}}(\eta)} = \frac{\mathcal{S}_\perp(\eta)}{c_\perp^2(\eta)\bar{t}_{\text{web}_s}\left(\bar{h}_{fspar} + \bar{h}_{rspar}\right)}$$

$$\sigma_{\text{cap}} = \frac{\mathcal{M}_\perp(\eta) h_{max}}{2(I_{\text{cap}} + r_E I_{\text{web}})} \simeq \frac{\mathcal{M}_\perp(\eta)\bar{h}_{max}}{2c_\perp^3(\eta)\bar{I}_{\text{cap}}}$$

Energy-Aware Aerial Systems for Persistent Sampling and Surveillance

E. W. Frew, Brian Argrow- U of Colorado-Boulder; Adam Houston – U of Nebraska-Lincoln)
Chris Weiss - Texas Tech University

Approach/Methods

T1 Wind Sensing and Energy Estimation

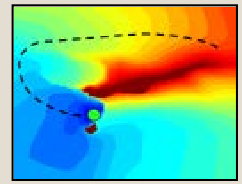
Integrate new hardware and algorithms for measuring wind field and platform state.

- Integrate a multi-hole probe into the Tempest UA
- Combine air data with aircraft state estimates to determine total aircraft energy state
- Implement real-time processing of data sets from multiple Doppler radar to determine 3-D wind field

T2 Models for Online Planning

Develop models of the wind field aloft that can be used in planning loops.

- Implement spatio-temporal Gaussian processes for wind velocity prediction from onboard measurements.
- Derive atmospheric models for online planning (AMOP) of variable complexity
- Assess AMOP off-line against high-performance simulation results.



T3 Hierarchical Guidance and Control

Design a guidance and control framework that switches algorithms based on the model abstractions.

- Implement low-level gust responsive control and high-level rapidly-exploring random forests.
- Create receding horizon control algorithms that adapt the planning horizon and cost approximation.
- Design adaptive, dynamic ordered upwind methods using wind field mesh data produced by the Doppler radar and AMOP.

T4 Experimental Validation

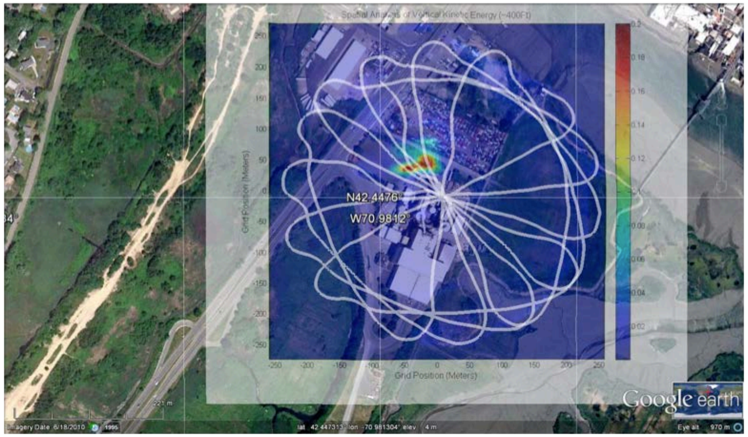
Validate all algorithms and techniques on meaningful field experiments.

- Integrate Doppler radar and atmospheric model into existing UA command and control middleware software.
- Validate algorithms and subsystems through small-scale experiments
- Evaluate full system through a primary mission scenario that will include surveillance of a road network and tracking unknown targets..

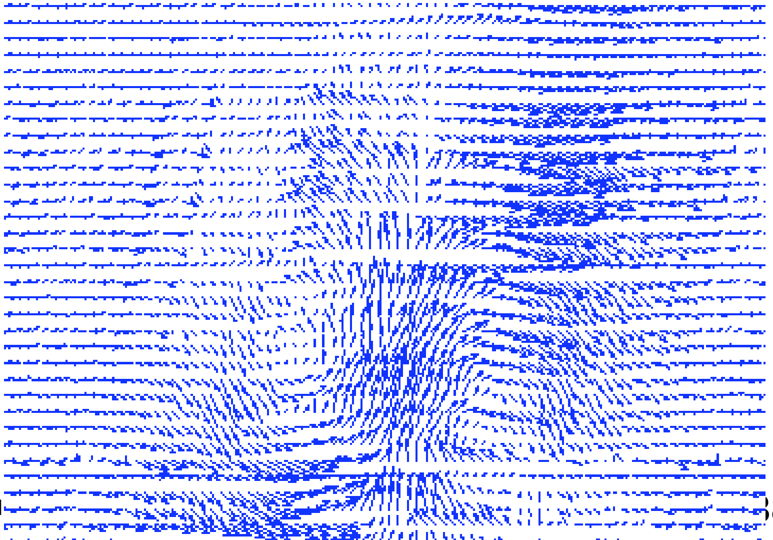
Fluid-SLAM

Sai Ravela, Choi, Jonathan How, MIT

Adaptive sampling with Gaussian Process to reconstruct plume kinetic energy



The estimated flow is used for efficient flight



Project Highlights of Work To Date

- Bottom-Up
  - Aircraft selected (X-8)
  - Autopilot Control Laws (Open Source)
  - Public Simulator
  - Hawai'I Volcano Study
  - Coordination with NASA Wallops Island Flight Facility
- Top Down
  - Running versions of SAM
  - New techniques to quantify uncertainty for coherent structures
  - Gaussian Process Adaptive Sampling
  - Flow-dependent path planning

Fluid-SLAM

Sai Ravela, Choi, Jonathan How, MIT

- **Theory: Variational Information-theoretic Scale-Adaptive Inference (VISI)**
- **Methodology: Tight integration of Modeling Estimation, Sampling, Planning, and Control (MESPAC)**
- **Application: Localization and Mapping of Coherent Atmospheric Structures: Thermals, Plumes and Shallow Cumuli to initiate a detailed cloud database.**

an X8 UAS used to study Kilauea plume, Jan 2013

Approach

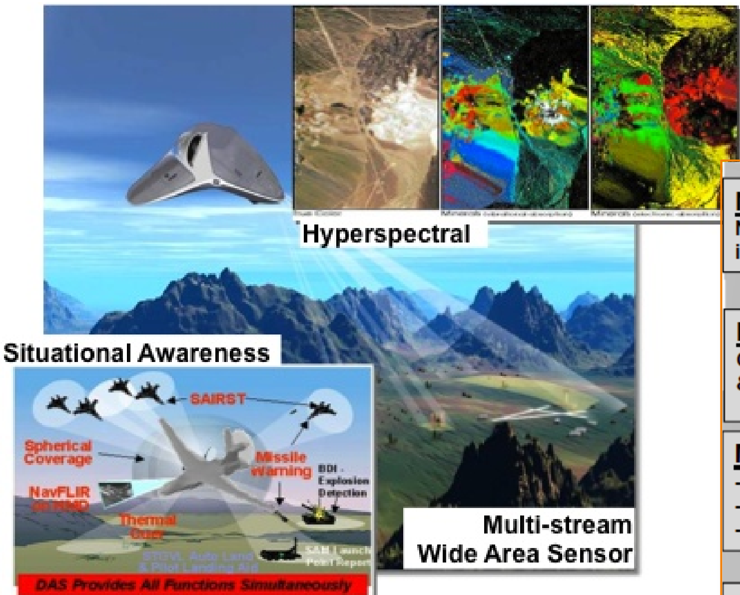
- Theory: Time-dependent variational inference without (a) linearization, (b) sampling/resampling, and using (c) kernels, (d) tractable information measures and (e) multi-scale structure.
- Methodology: Primary measurements constrain a simplified model, which seeds a detailed model whose instabilities and uncertainties are reduced by adaptive sampling, that is planned by respecting flow, energy, timing and communication constraints and implemented by cooperative control among multiple UAS platforms. The tight coupling of this DDDAS cycle is accomplished by using a uniform information-theoretic formulation.
- Application: Parametric thermal/plume/cloud models initiate flows in SAM/WRF. Adaptively constrained model returned as analysis of coherent structure, which will then be used to study the accuracy of the development of cumulus structure in numerical models.

Application of DDDAS Principles to Command, Control and Mission Planning for UAV Swarms

M.B. Blake, G. Madey, C. Poellabauer – U. Of Notre Dame

Advancing ISR Capabilities

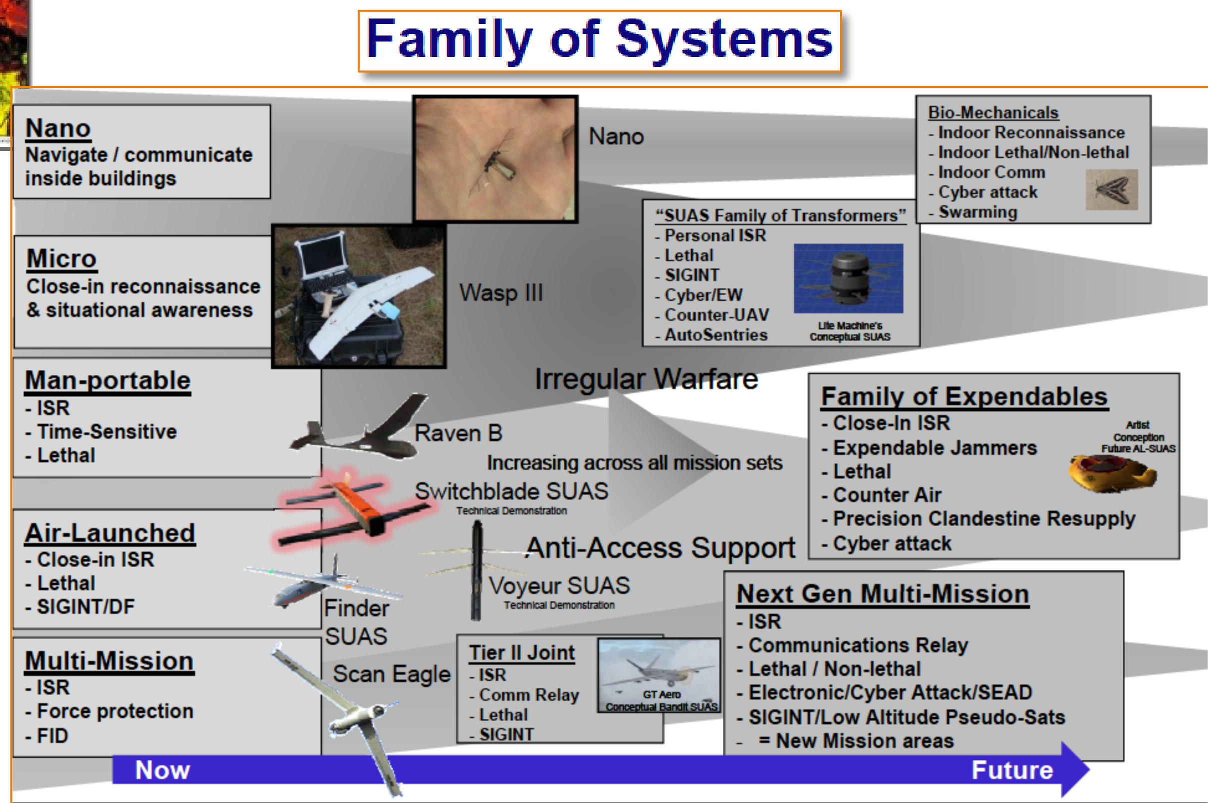
Intelligence, Surveillance, Reconnaissance
Situational Awareness
Wide Area Airborne Surveillance (WAAS)



Complex UAV Missions

- Cooperative Sensing
  - HUMINT
  - SIGINT
- Mixed Platforms / Capabilities
- Cooperation with Air and Ground Forces
- Dynamic Adaptive Workflows
- Adaptive Sensing, Computation, Communications

Heterogeneity: Micro and Nano-sized Vehicles, Medium "fighter sized" Vehicles, Large "tanker sized" Vehicles, and Special Vehicles with Unique Capabilities



Lt. Gen. Deptula, 2010

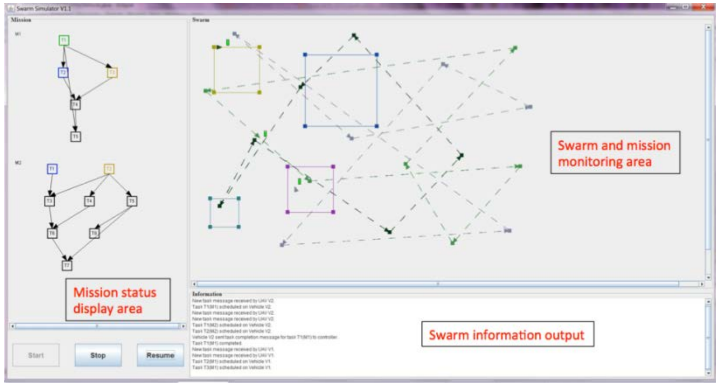
AFRL

Application of DDDAS Principles to Command, Control and Mission Planning for UAV Swarms

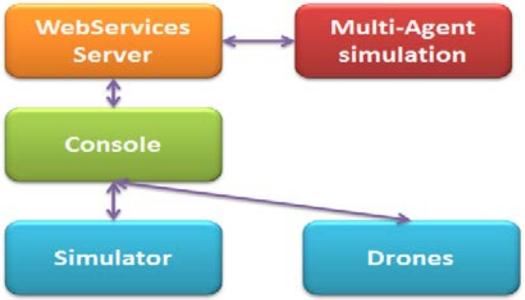
M.B. Blake, G. Madey, C. Poellabauer – U. Of Notre Dame

Project Highlights of Work To Date

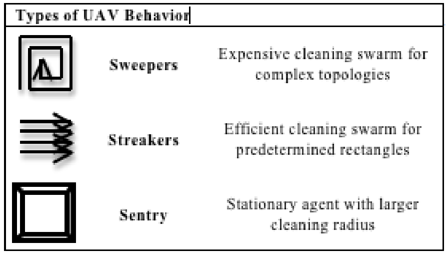
Swarm Task Assignment For Mission Planning



Modular Test Bed

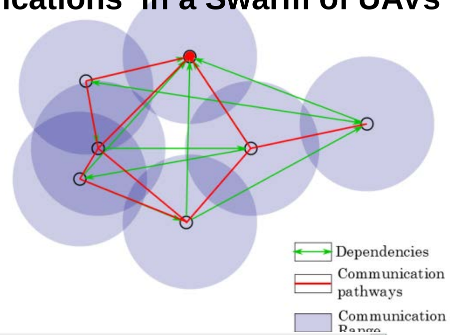


UAV Cooperative Search

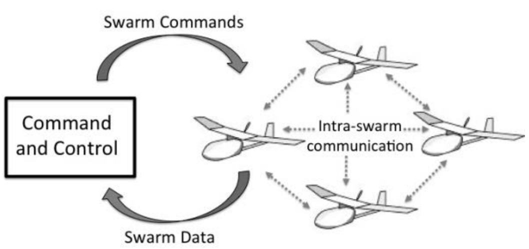


Types of UAV Behavior		
	Sweepers	Expensive cleaning swarm for complex topologies
	Streakers	Efficient cleaning swarm for predetermined rectangles
	Sentry	Stationary agent with larger cleaning radius

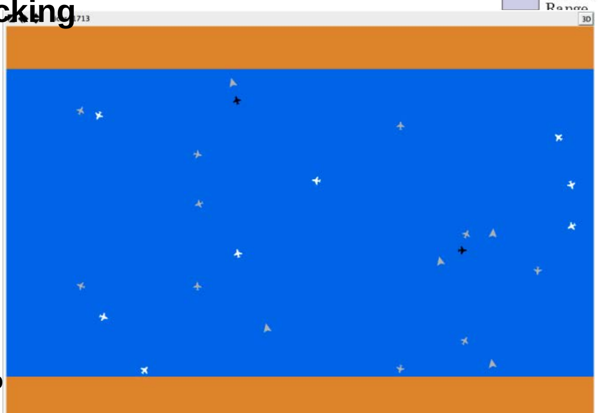
Simulating Multi-hop Communications in a Swarm of UAVs



Flying the Swarm Rather than the UAVs



UAV Mission Vessel Tracking

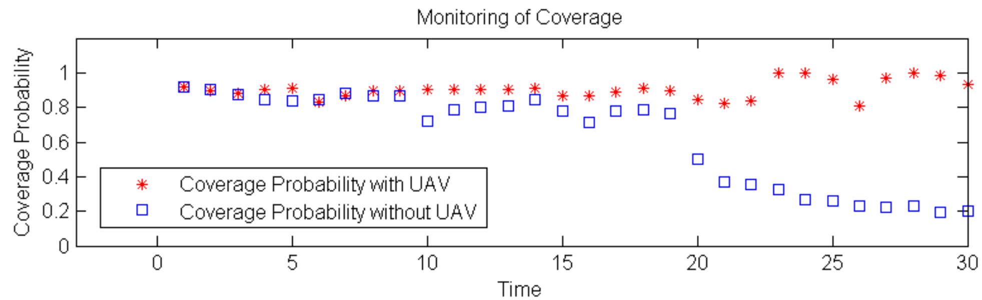


DDDAMS-based Urban Surveillance and Crowd Control via UAVs and UGVs

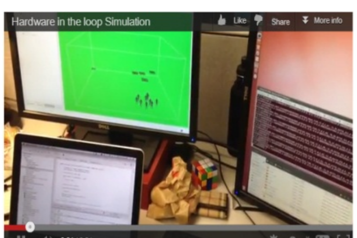
Young-Jun Son, Jian Liu, University of Arizona; Jyh-Ming Lien, Computer Science, George Mason University

Project Highlights of Work To Date

- **Task 1: Development of algorithms**
  - **Preliminary results obtained (see below), where coverage (% of targets under control) with UAV/UGVs is highly improved compared with that of UGVs only**
  - **Future plan: continue to enhance algorithms and test them with more complex scenarios (hardware-in-the-loop environment)**

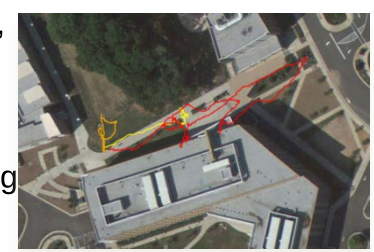


- **Task 2: Development of hardware-in-the-loop platform**
  - **A hardware-in-the-loop simulation with UAV has been established (see 1st figure)**
  - **2 UAVs both at Arizona and GMU have been developed and tested (see figures below)**
  - **Future plan: Expand testbed with UGVs, and use it to test enhanced algorithms**



Hard-ware-in-the-loop simulation; video available at http://sie.arizona.edu/CIM/AFSOR_project.html

Includes battery, GPS, telemetry. Can handle an additional payload of 1200g



Recorded path from Google map; video available at *http://masc.cs.gmu.edu/wiki/UAV*

DDDAS Systems Software

PCPAD-X (Processing, Collection, and Dissemination)

AFOSR LRIR – *Erik Blasgen, Guna Seetharaman, RI Directorate, AFRL*

- **Collaboration:** RY (Sensors), RI (Information), RH (Human Effectiveness)